NTNU
Norwegian University of Science and Technology

Faculty of Engineering Science and Technology
Department of Hydraulic and Environmental Engineering

M.Sc. thesis in

Hydraulic and Environmental Engineering

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Title: Impacts on future climate on hydropower resources

1 BACKGROUND

Studies based on older climate scenarios shows that the Norwegian hydropower system in general will receive more inflow but with a changed seasonal distribution. This will have implications on how the system is operated and also for the river environment due to changes in flow. This will most likely also lead to changes in mitigation practices and new mitigation measures might be needed in the future. Planning hydropower infrastructure is done for 40 or more years into the future, and an overview of possible changes in the future is therefore important.

In 2013, IPCC released the 5th assessment report (AR5) with a set of new climate scenario simulations from Global Circulation Models. These are based on a new way of describing the effect of future emissions, representative concentration pathways (RCPs). A considerable amount of work is done with the old 4th report setup, and there is a need to find out both how the system responds to the new scenarios and how past assessments correspond with the AR5 scenarios.

The purpose of this project is to downscale new climate data to the station level and see how these compares to the RCM predictions, to the past report scenarios and then to apply the downscaled data to two hydropower systems in Norway giving some regional variation in the data.

2 MAIN QUESTIONS FOR THE THESIS

1. Downscaling of climate data based on the CORDEX database.
    a. Literature review of current methodologies for downscaling to the station level. Further, review the CORDEX data and their direct application for delta change methods.
    b. Select a method based on 1-a and downscale data for a select number of stations (to be determined later).
    c. Prepare delta change values based on the CORDEX data for comparison.

2. Assessment of downscaled precipitation and temperature values.
    a. Compare the downscaled values for gauge sites within one RCM grid with the corresponding delta-change values for the same grid cell based directly on the RCM (using Netra Timalsinas method).
    b. Compare the downscaled station based data with the previous A1, B1, B2 scenarios from the Norwegian meteorological institute.
    c. Select the data to use for task 3. Decide if current scenario simulation allows for direct use or if the delta change methods is also necessary for the station data.

3. In task 3 the data from 2) should be used in setting up a hydropower simulation. To make it possible to realize within the timeframe of the project we will not set up the hydropower models but use an already existing system.
    a. Select the system to be used and provide an overview of the hydropower system based on the existing nMag model.
    b. Based on the data from 2), compute the inflow to the selected systems for all downscaled scenarios
    c. Run nMag with the current scenario and the future scenarios and evaluate changes in the results.
    d. Provide a synthesis of changes in and between the two systems.

3 SUPERVISION, DATA AND INFORMATION INPUT

Professor Knut Alfredsen will be the main supervisor for the work. Dr. Roser Casas-Mulet will be working with the MSc candidate on developing the downscaling methods.

Discussion with and input from colleagues and other research or engineering staff at NTNU, SINTEF, power companies or consultants are recommended. Significant inputs from others shall, however, be referenced in a convenient manner.

The research and engineering work carried out by the candidate in connection with this thesis shall remain within an educational context. The candidate and the supervisors are therefore free to introduce assumptions and limitations, which may be considered unrealistic or inappropriate in a contract research or a professional engineering context.

4 REPORT FORMAT AND REFERENCE STATEMENT

The thesis report shall be formatted for the DAIM system. The report shall include a summary, a table of content, lists of figures and tables, a list of literature and other relevant references and a signed statement where the candidate states that the presented work is his own and that significant outside input is identified.

The report shall have a professional structure, assuming professional senior engineers (not in teaching or research) and decision makers as the main target group.

The thesis shall be submitted no later than ______ 20__.

Trondheim 24th of August 2014

____

Knut Alfredsen

Professor

Author’s statement

I hereby declare that this Master Thesis has been carried out by my own work, and that the sources have been fully referred in the text.

Trondheim, February 2015

Carles Palou Anglès

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I would like to thank my supervisor, Professor Knut Alfredsen, Department of Hydraulic and Environmental Engineering, Norwegian University of Science and Technology, for all his support, guidance and availability during all the stages of this thesis. His continuous suggestions and advices have been very helpful in preparing this report.

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Finally, I would like thank everyone who has enabled me to work in such an interesting project and enriching experience in Norway. Writing the master thesis abroad have given me the opportunity to discover new ways of working and the chances to get into new tools which were completely new to me.

Abstract

The Intergovernmental Panel on Climate Change (IPCC 2013) concluded with high confidence that the atmosphere is warming because of the anthropogenic activities and this fact can affect to the climatic conditions. Considering that the 99% of total energy produced in Norway comes from hydropower, it is essential to predict the future climatic conditions in order to be able to anticipate and design the future hydropower systems to manage the water resources. This study is carried out in the south of Norway, in 3 different stations of Vest-Agder County.

The Regional Climate Models (RCM) are downloaded from Coordinated Regional Climate Downscaling Experiment (CORDEX) with a total of 5 models and 9 scenarios, according the new scenarios described in 5th assessment report (AR5). These models are used to perform an assessment. Further downscaling is needed for hydrology processes, so a bias correction method by Torill Engen-Skaugen is applied to dynamically downscaled precipitation and temperature. Then, these outcomes are compared to the observed data, the station values with delta change applied, and old scenarios described in the Special Report on Emissions Scenarios (SRES) in 2007. In the case of temperature, the bias correction Engen-Skaugen method is found satisfactory but the same adjustment in precipitation does not perform very well.

After, the Hydrologiska Byråans Vattenbalansavdelning (HBV) is chosen to proceed with the thesis. The model calibration is done based on the real observation data from Kjevik station and Myglevatn river flow in the period 1995-2000 obtaining a R^2 value of 0.71 and validated in 3 different five-years periods. Next, statistically downscaled data from Kjevik is selected to proceed running all models and scenarios with the HBV. A slight increase in addition to seasonal changes is found in runoff and a significant decrease of the snowpack and snowmelt are predicted for that location in the future period (2071-2100).

Finally, runoff outputs from HBV are used as an input for the Nmag model in the Mandal catchment. The study focus on the Laudal power plant, situated in the lowest point of the mentioned catchment, and how can it be affected according to these future predictions. Not only seasonal changes are found in the inflow but also an increment in the total annual inflow. Besides that, a modest increment is predicted in the future annual power production in Laudal.

In conclusion, this study has been successfully carried out not only how the global warming will impact Vest Agder County and the Laudal power plant in the future, but also to examine the results of the application of the Engen-Skaugen bias correction method for local scales and the comparison to other downscaling methods.

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List of abbreviations

CORDEX	Coordinated Regional Climate Downscaling Experiment
DC	Delta Change
ES	RCM_{future} bias corrected
ESH	RCM_{hist} bias corrected
GCM	Global Climate Model
HBV	Hydrologiska Byråans Vattenbalansavdelning
HESS	Hydrology Earth System Sciences
IPCC	Intergovernmental panel on Climate Change
Km^2	Kilometer square
m^3/s	Cubic meter per second
masl	Meter above sea level
mm	Millimeter
Mw	Power production Megawatts
nMag	A computer program for hydropower simulation
NMI	Norweign meteorological instutute
NoSerC	Norwegian Service Centre for Climate Modelling
NVE	Norges vassdrags- og energidirektorat
OBS	Observed data
OS	Old Scenarios
R^2	Nash-Sutcliffe coefficient
RCM	Regional Climate Model
RR	Precipitation
SMHI	Swedish Meteorological and Hydrological Institute
SRES	Special Report on Emissions Scenarios
TEMP	Temperature
WCRP	World Climate Research Programme

1 Introduction

1.1 Context

The 5th assessment report (AR5) published in 2013 (IPCC 2013) by Intergovernmental panel on climate change (IPCC) provides a current state of scientific knowledge relevant to climate change. It concludes that atmosphere is warming because of the anthropogenic activities and declares that climate change is a real problem due to the amount of greenhouse gases that are released to the atmosphere all over the world as shown in the Figure 1-1.

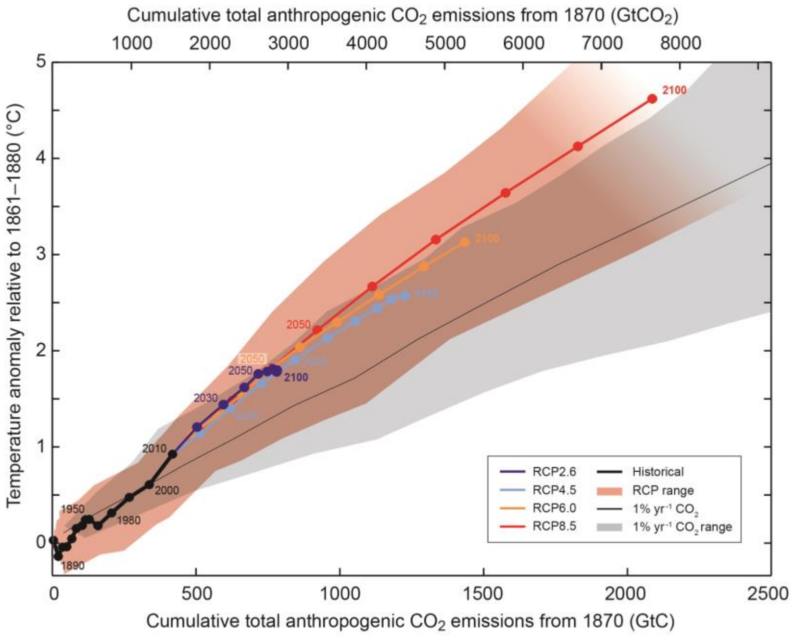


Figure 1-1 Graph extracted from the IPCC 5th Report where temperature anomaly relative to 1861-1880 is plotted against the cumulative total anthropogenic CO_2 emissions from 1870 categorized by the new scenarios presented in the mentioned report

In general sense, Norway will be also affected by the climate change. The center for international climate and environmental research of Oslo (CICERO) and the research program Regional climate development (RegClim) point an increase of precipitation in Norway and the temperature is expected to rise over the whole country. In addition, the snow storage and the depth of frozen ground is expected to decrease (Schuler, Beldring et al. 2006).

These variations, apart from affecting the conditions of the seas and the forests altering the ecosystems of several animals as points the Norwegian environment agency, are very influential in Norway, where the 99% of total energy produced in Norway comes from hydropower, a very vulnerable resource to climate change. Hence, it is necessary to examine how these changes can affect to the current hydropower systems in order to be able to adjust and redesign the current system. In general, projections in Norway locations not only indicate an increase of the energy generation (Haddeland;, Røhr; et al. 2011; Chernet, Alfredsen et al. 2013) but also show moderate changes in annual streamflow and seasonal streamflow changes (Beldring, Colleuille et al. 2005).

Global climate models (GCMs) are the primary tool to predict how the global climate may change but they do not solve small-scale climate features. Thus, the need of downscaling GCMs to Regional climate models (RCMs) is essential to be applicable at regional scale. However, the effect of topography is not well captured with the RCM resolution and it does not grant reliable data on hydrological processes occur at finer scales (Kundzewicz 2007). Therefore, the necessity to apply bias correction methods can help in order to reach better results and hence, to be able to manage and plan hydropower systems.

In the current thesis, a method for adjusting dynamically downscaled precipitation and temperature from the RCM from CORDEX with the new scenarios presented in the 5^{th} assessment report (Engen-Skaugen 2007) has been applied.

1.2 Literature review

1.2.1 Downscaling

Many techniques have been developed to transfer the GCMs output from coarse spatial scales to regional scales adding considerable value to these projections (Maraun 2010). These downscaling techniques can be classified into two main categories: "statistical downscaling methods", based on developing statistical links between large-scale atmospheric variables and observed daily local data (Piani 2010), and "dynamical downscaling techniques", based on physical or dynamical links between the climate at large and at smaller scales to simulate finer-scale physical processes (Giorgi, Christensen et al. 2001) such as RCMs. Deep analysis and comparison between different methods have been further developed (Hanssen-Bauer, Førland et al. 2003; Fowler, Blenkinsop et al. 2007; Gudmundsson L. 2012).

Amongst the various statistical approaches, empirical downscaling methods are the most commonly used due to their ease of implementation. In this current report, a statistical downscaling method is used, the widely known delta change approach (H. J. Fowler 2007), which predicts future climate time series by perturbing the historical observed climate data with change factors based on RCM future and historical simulations.

The RCMs spatial resolution (typically 50 x 50 km^2) is still too coarse to be representative locally. The terrain in the RCMs is smoothened and the sites elevation is not well represented. Thus, its use in hydrological climate change studies, where the orography is very influential, is challenging due to the risk of considerable biases. In order to deal with this biases, several bias correction methods and approaches have been recently developed (Teutschbein and Seibert 2012; Lafon, Dadson et al. 2013) though they have to be applied properly (Ehret, Zehe et al. 2012).

In this context, large number of uncertainties is presented. For instance, statistical downscaling presents a large uncertainty associated with the choice of a given empirical downscaling method (Chen J. 2013). It is also underlined the importance of using several climate projections for empirical downscaling approaches to delineate uncertainty when assessing the climate change impacts on hydrology.

The main assumption in statistical downscaling is that the statistical relationships identified for the current climate will remain valid under changes in future conditions, nevertheless these approaches help to quantify the relative significance of different sources of uncertainty affecting water resources in the future (Kundzewicz 2007).

Although the application of RCM simulations is a challenge due to often biases, progress in regional climate modeling has made their more attractive. The application of bias-correction methods is recommended, although one must be aware that the need for bias corrections adds significantly uncertainties in modeling climate change impacts (C. 2010).

The current thesis will include the application the Engen-Skaugen bias correction method (Engen-Skaugen 2007) with a later analysis and comparisons with other downscaling techniques.

1.2.2 Hydrology

Studies of the impact of climate change have already been developed in Norway, where orography has a main importance. Generally, projections announce an increase of 11-17% annual inflow with earlier peaks (Chernet, Alfredsen et al. 2013). Moderate changes in annual streamflow and seasonal changes are predicted in the central and south of Norway (Beldring, Colleuille et al. 2005). Other studies indicate not only an increase in winter discharges and earlier snowmelt floods but also an increase in autumn discharge (Hisdal, Holmqvist et al. 2010).

1.2.3 Scenarios

In the IPCC report (AR5) a set of new climate scenarios simulations are adopted based on a new way of describing the effect of future emissions: the representative concentration pathways (RCPs) (Wayne 2013). An overview of them is presented below:

Name	Radiative forcing	CO_2 equivalent (p.p.m.)	Pathway
RCP 8.5	8.5 Wm^2 in 2100	1370	Rising
RCP 6.0	6.0 Wm^2 in 2100	850	Stabilization without overshoot
RCP 4.5	4.5 Wm^2 in 2100	650	Stabilization without overshoot
RCP 2.6	3 Wm^2 before 2100 declining to 2.6 Wm^2 in 2100	490	Peak and decline

Table 1-1 Representative Concentration Pathways (RCPs)

One of the aims of the current thesis is to find how the system responds to the new scenarios and how past assessments correspond with the AR5 scenarios.

On the other hand, in the SRES (IPCC 2007), another way of characterize future scenarios was described. Assumptions about future technological development as well as the future economic development are thus made for each scenario. They are organized into families, A1, A2, B1, B2, which contain scenarios that are similar to each other in some aspects.

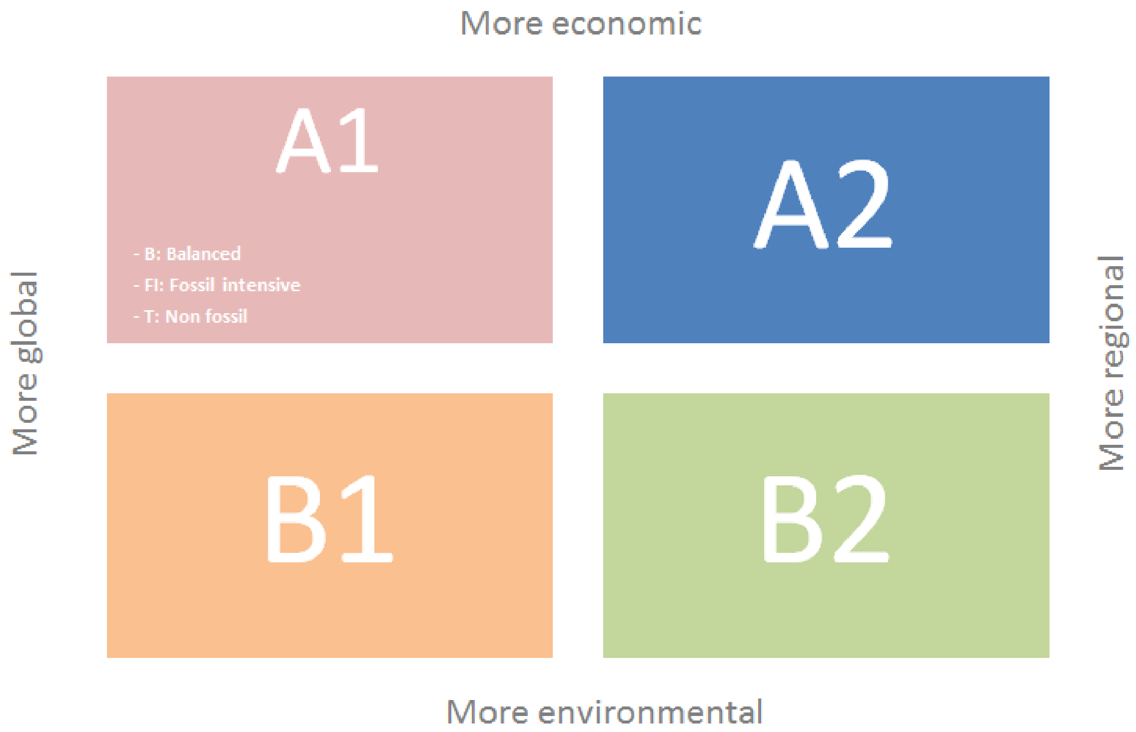


Figure 1-2 The four main SRES categories: A2 and B2 were the main scenarios used in the IPCC Third Assessment Report and later A1B has been the most common scenario. A1FI is the most extreme scenario regarding emission rate.

The A1 describes a future world of very rapid economic growth, global population that peaks in 2050 and declines afterwards, and the rapid introduction of new and more efficient technologies. Convergence among regions is also a feature of this scenario. It is divided into 3 subgroups depending on the direction of the technological change and energy system. On the other side, A2 describes world more heterogeneous. It is represented by a world more independently operating with self-reliant nations and an increment of the population. Economic development is primarily regionally oriented with and slower technological change.

The B1 and B2 scenarios are more environmentally focused. On one hand, B1 represents an integrated and ecological friendly scenario with a global population that peaks in 2050 and declines afterwards. There is a reduction of the material intensity and emphasis on global solutions to economic, social and environmental stability. On the other hand, B2 defines a divided and ecologically friendly scenario. There is a growth of population, slower rate than A2, and emphasis on local and social, economic and environment stability. It is characterized by intermediate levels of economic development, and less rapid and more diverse technological change than in B1 and A1.

1.3 Objective of the study

The main objective of this study is to downscale the climate data to the station level. For that purpose, the Engen-Skaugen correction (Engen-Skaugen 2007) is performed, the delta change is calculated and applied to the station data and a comparison between them and with the results of the old scenarios are performed. Afterwards, the most reliable data is selected and used as an input in HBV. Finally, nMag is run to analyze how the future scenarios can affect to the hydropower system in Mandal catchment.

1.4 Scope of the study

The next tasks will be performed to meet the objectives:

- Literature review of current methodologies for downscaling to the station level.
- Downscale the data and apply the Engen-Skaugen method bias correction.
- Apply delta change to the station data values based on the RCMs from CORDEX and prepare them for comparison.
- Acquisition of old scenario values and preparation for comparison.
- Detailed comparison between Engen-Skaugen, delta change and old scenarios.
- Decide if current scenario simulation allows for direct use or if the delta change methods is also necessary for the station data.
- Calibration of Pine HBV model in Myglevatn catchment.
- Model validation and run Pine HBV to obtain future simulated runoff.
- Run nMag with the current scenario and the future scenarios and evaluate changes in the results.

1.5 Methodology

This reports covers all the necessary tasks that were carried out to perform the impacts on future climate on hydropower resources. The assessment has been approach according to the study site, the method for adjusting dynamically downscaled precipitation and temperature, the hydrological model and the catchment selected. The Figure 1-3 below illustrates all the steps that have been performed in the study.

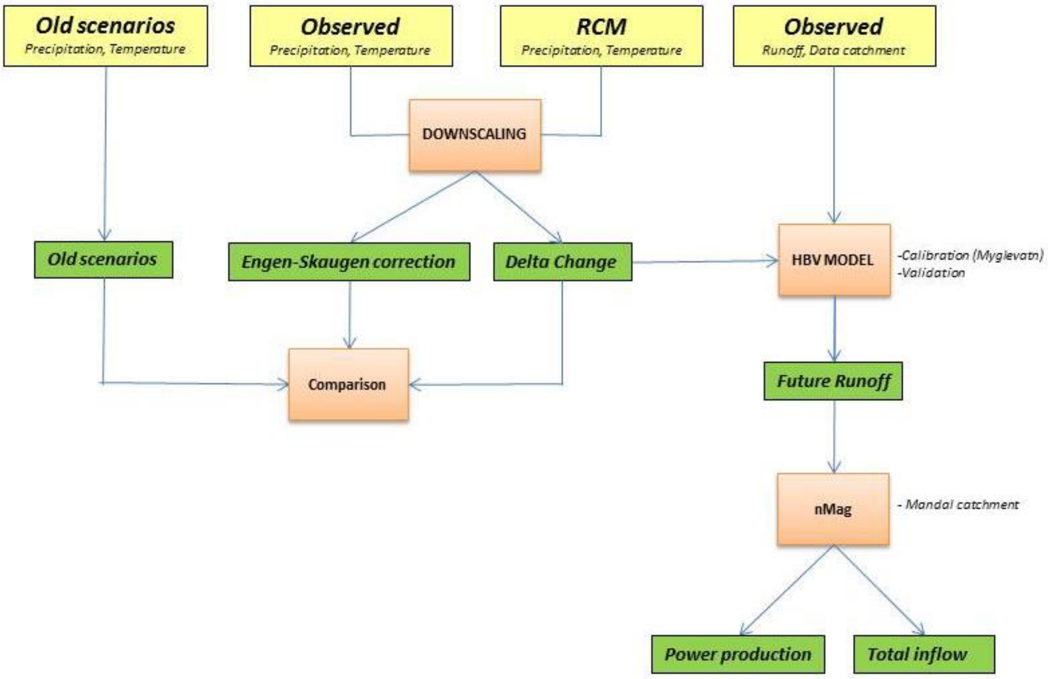


Figure 1-3 Scheme of the steps of the study with its main inputs and outputs

1.6 Structure

This report tries to cover all the necessary work that needs to be carried out to meet the objectives of the study. In general, each chapter is divided in subsections, beginning with an introduction, followed by the methodology and ended with results and the corresponding discussions and conclusions. The related theory is further explained also in respective chapters.

Chapter 1 gives a short introduction about the need of downscaling at local scales for hydrology studies and explains the context in Norway. Besides, objective and scope of the study, methodology and structure are defined.

Chapter 2 shortly presents the main study site of the thesis though more particular catchments are further explained on the corresponding section.

Chapter 3 includes all the steps for the downscaling procedure with all the calculations carried out and a detailed explanation of the scripts performed. The comparison between all the outputs as well as the results and conclusions are illustrated.

Chapter 4 explains the HBV model theory, the model calibration, the model validation and the results obtained discussed.

Chapter 5 describes the nMag model and the hydropower model system used, the methodology, the results and the conclusion of the most relevant point.

Chapter 6 includes main conclusions of the study

2 Study site

The current study is developed in Vest-Agder County, located in the south-west part of Norway. The total area is 7.281 km^2, which almost 10% is composed by a lot of lakes and rivers having 6 valleys that end on the coast. The northern part is mountainous and in the central part, fields and moors are more common.

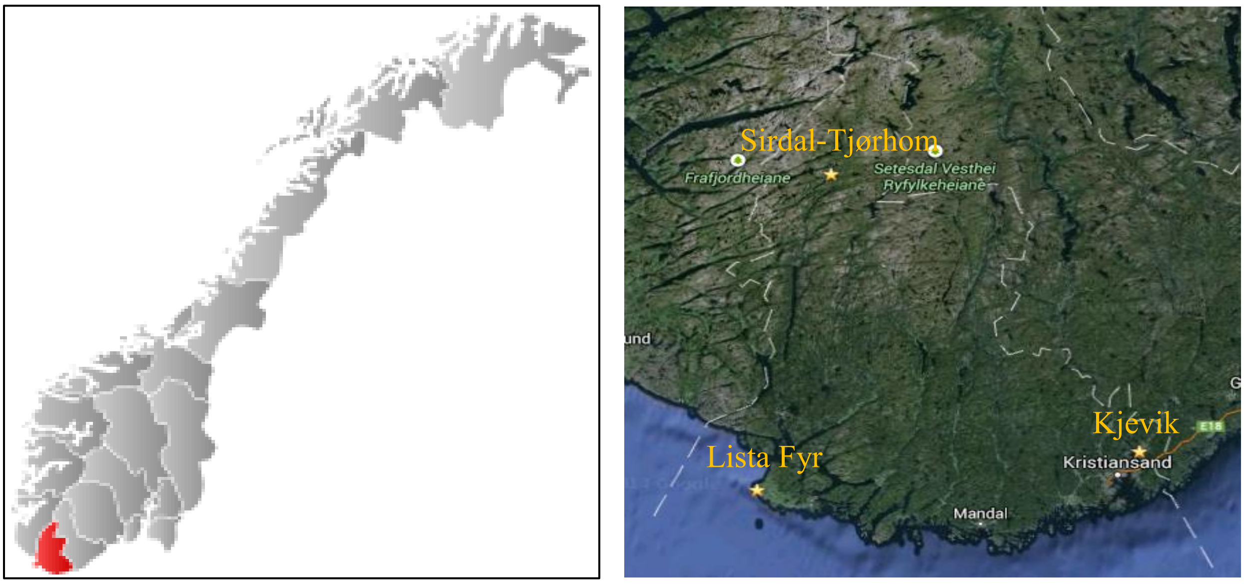


Figure 2-1 On the left, Vest-Agder within Norway and on the right, the three stations selected inside the Vest-Agder County.

In order to get a reliable representation of the area, three stations have been selected whose features are presented in Table 2-1. The selection has also been performed according to the old data available of each station.

Name of station	Longitude	Latitude	Height (m)
Sirdal -Tjørhom	6° 50' E	58° 53' N	500
Lista Fyr	6° 34' E	58° 6' N	14
Kjevik	8° 4' E	58° 12' N	12

Table 2-1 Selected stations' latitude, longitude and height

As we move ahead, several locations and catchments where calibrations, verifications and calculations will be developed are further explained on the corresponding section.

3 Downscaling of climate data

3.1 Introduction

The RCM of the following models have been downloaded from CORDEX and have been used to perform the future climate outputs:

- CNRM (*Centre National de Recherches Météorologiques*, France): It is a climate model developed in France by the *Centre National de Recherches Météorologiques*.
- ICHEC (Irish Centre for High-End Computing, Ireland): The Irish Centre for High-End Computing has worked on a climate model.
- IPSL (*Institut Pierre Simon Laplace*, France): The *Institut Pierre Simon Laplace* (IPSL) is a governmental funded research center devoted to research in the climate system and global environment. Since 1995, the IPSL Climate Modelling Centre (ICMC) develops climate models and performs simulations with them in order to improve our understanding and our knowledge of the climate, of its current characteristics and of its past and future changes.
- MOHC HADGEM2 (Hadley Centre Global Environment, United Kingdom): The HadGEM2 family of climate models represents the second generation of HadGEM configurations.
- MPI ESM (Max Planck Institute for Meteorology, Germany): The MPI-ESM is a comprehensive Earth-System Model, in the sense that it couples the ocean, atmosphere and land surface through the exchange of energy, momentum, water and important trace gases such as carbon dioxide.

In the current study, the models and scenarios included are shown in the following table:

<table>
<tr><th></th><th>Model</th><th>Scenarios</th></tr>
<tr><td rowspan="9">New scenarios</td><td rowspan="2">CNRM</td><td>RCP 4.5</td></tr>
<tr><td>RCP 8.5</td></tr>
<tr><td rowspan="3">ICHEC</td><td>RCP 2.6</td></tr>
<tr><td>RCP 4.5</td></tr>
<tr><td>RCP 8.5</td></tr>
<tr><td>IPSL</td><td>RCP 8.5</td></tr>
<tr><td rowspan="2">MOHC_HADGEM2</td><td>RCP 4.5</td></tr>
<tr><td>RCP 8.5</td></tr>
<tr><td>MPI_ESM</td><td>RCP 8.5</td></tr>
</table>

<table>
<tr><th></th><th>Model</th><th>Scenarios</th></tr>
<tr><td rowspan="2">Old scenarios</td><td rowspan="2">HADM</td><td>A2</td></tr>
<tr><td>B2</td></tr>
</table>

Table 3-1 Old scenarios from SRES and news scenarios from AR5 included in the thesis

The old scenarios data is gathered from Norwegian Service Centre for Climate Modelling (NoSerC). In order to continue, 1 model with 2 scenarios are selected from the old scenarios and 5 models with a total of 9 scenarios of the new scenarios are selected (Table 3-1)

3.2 Structure

The aim of the structure of this part of the thesis, apart from downscale the data and applying the bias correction method, is to reach to a common format in order to perform a final comparison. The differences between the predicted scenarios and the old scenarios will be analyzed.

Therefore, to achieve the same layout, 4 steps are developed as following:

- Step 1: Extraction of the point data based in the selected catchment
- Step 2: Extract the relevant precipitation and temperature
- Step 3: Calculations
    - Step 3.1: Predicted future station data with delta change, using new scenarios
    - Step 3.2: Predicted future station data with Engen-Skaugen corrections, using new scenarios
    - Step 3.3: Predicted future station data using old scenarios
- Step4: Comparison of all data

3.3 Methods

3.3.1 Step 1: Extraction of the point data based in the selected catchment

The purpose of this first step is to obtain the RCM points that fall into the shape file that has been chosen. Before running the script, there is a necessity to select the stations we are interested in (Kjevik, Lista Fyr and Sirdal) in order to create the corresponding shape file, which will be one of the inputs to the current script. The file has to contain the area around the stations in order to be able to choose the RCM point data which will fall closer to the selected stations.

ArcGIS software is used to compare the shapes, visualize them and decide which point is the best. The appendix A can be read for details on how to make the point and area shape files.

The script "1.Extraction_of_points_Index_in_the_basin_step_1", written by Netra Prasad Timalsina, a PhD from the hydraulic and environmental engineering department of the NTNU, is summarized in the Table 3-2.

Name of the script	1.Extraction_of_points_Index_in_the_basin_step_1
Number of scripts	1
Function	This script finds the location of the points based on the catchment. The output of this script is the index of the matrix of variable by which we can extract only those located within the basin. This script only needs to be run once.
Input files	• Shape files (*.shp): Selected study area with latitude as X and longitude as Y and RR as Z dataset. To convert to latitude and latitude projection see *Appendix 1* • Nc files (*.nc): Any of the *.nc files can be used for it as they all have the same base information needed in this stage.
Input files location	*C:\CLIMADOWN\Step1\Input*
Output files	• Rdata files (*.Rdata): index_of_the_3d_matrix • Xls files (*.xls): rr_final
Output files location	*C:\CLIMADOWN\Step1\Output\index_of_the_3d_matrix.Rdata* *C:\CLIMADOWN\Step1\Output\rr_final.xls* And two folders: *C:\CLIMADOWN\Step1\Cross_section_shape_poly* *C:\CLIMADOWN\Step1\Node_Shapefile*

Table 3-2 Information about script step 1

Among other outputs, the script 1 results in the "rr_final.xls", file which can be used to select the RCM points that fall closer to the stations. The mentioned file must be converted to a shape file to be able to visualize the location of the points in relation to the existing stations.

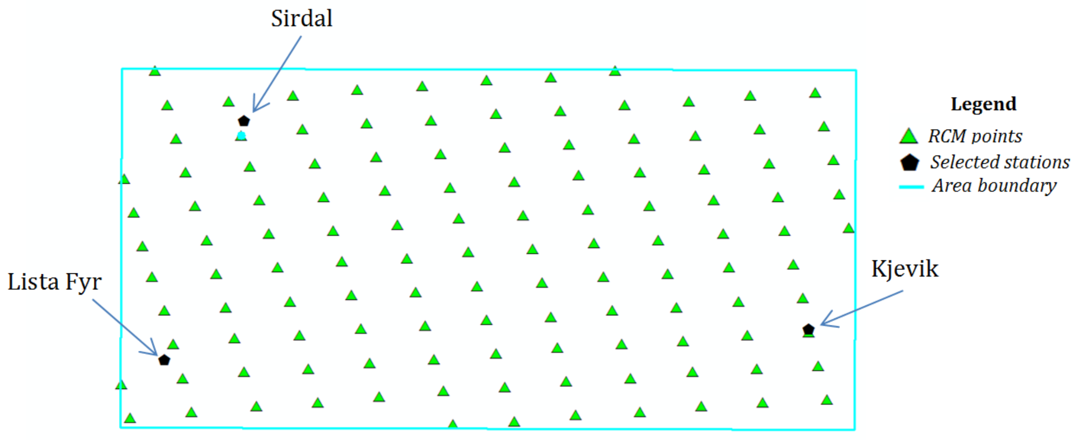


Figure 3-1 ARCGIS area that includes all the selected stations and the RCM points

The “rr_final.xls” file has 3 types of information for each RCM point that falls into the catchment (identification number, longitude and latitude). Therefore, the “rr_final.xls” should look similar like Table 3-3.

Code	"longitude"	"latitude"
"119351"	7.51	57.89
"119352"	7.71	57.9
"119353"	7.91	57.92
"119354"	8.12	57.93
"119355"	8.32	57.95
"119356"	8.52	57.96
"119357"	8.73	57.97
"119770"	6.46	57.91
"119771"	6.66	57.93
"119772"	6.87	57.95

Table 3-3 Layout example of rr_final.xls

After comparing the RCM points to the stations, the codes from the RCM points closest to the stations are identified and listed in the Table 3-4.

Name of station	Code
Sirdal	123165
Lista Fyr	120619
Kjevik	120205

Table 3-4 Name of the station and its longitude, latitude and code

3.3.2 Step 2: Extract the relevant precipitation and temperature

The main purpose of this script is to extract the relevant daily data (precipitation and temperature) from the RCM points inside the selected area. It will create a text file (*.txt) and an Rdata file (*.Rdata) for each model, both for the historical data (hist) and for each scenario (2.6, 4.5, 8.5). These data will be later converted to monthly data, which will be lately used to extract delta change values. This script was also written by Netra Prasad Timalsina.

In order to be able to run the script correctly, there is a need to create all the folders that match to all the models and scenarios. It is also important to have the corresponding *.nc files in the folders of precipitation (RR) and temperature (TEMP) for each model and scenario. All *.nc files were taken from Netra Prasad Timalsina.

In this step, 2 different scripts have been created: one for all the models and another one for the MOHC_HADGEM2 model because the structure of the data demands it. In addition, it also have been computed separately the precipitation (RR) from the temperature (TEMP). Hence, there are 4 different scripts:

Name of the scripts	2.Extraction_of_variable_in_the_basin_rr_step_2A_AllModels *(Note: the other scripts have the same name except little changes due to their characteristics)*
Number of scripts	4 (rr/temp and AllModels/HAD) *(Note: rr/temp means that to compute temperature values (temp) instead of precipitation values (rr) the name of the script the word "temp" have been substituted for "rr"; similarly applied with the words "AllModels" instead of "HAD")*
Function	It takes the data needed to proceed to the next step such as the precipitation and the temperature from the RCM points inside the catchment. These scripts need to be run several times, as many models and scenarios are at the beginning of each script (11 times for "AllModels" and 3 times for "HAD").
Input files	• Rdata files (*.Rdata): index_of_the_3d_matrix. • Nc files (*.nc): It takes the *.nc files from the folder that it is currently running (the precipitation files name start with "pr" and temperature files name start with "tas")
Input files location	*C:\CLIMADOWN\Step1\Output\index_of_the_3d_matrix.Rdata* It is extracted from the corresponding folder: *C:\CLIMADOWN\Step2*
Output files	• Rdata files (*.Rdata): It is saved in the corresponding folder with the name due to the model, scenarios and current period. • Text files (*.txt): It is saved in the corresponding folder with the name according to the model, scenarios and current period.
Output files location	It is stored in the corresponding folder in: *C:\CLIMADOWN\Step2*

Table 3-5 Information about scripts step 2

In order to give a general idea of how the folders are classified:

Precipitation data (RR)	Temperature data (TEMP)
C:\CLIMADOWN\Step2\RR\CNRM_hist	*C:\CLIMADOWN\Step2\TEMP\CNRM_hist*
C:\CLIMADOWN\Step2\RR\CNRM_RCP_45	*C:\CLIMADOWN\Step2\TEMP\CNRM_RCP_45*
C:\CLIMADOWN\Step2\RR\CNRM_RCP_85	*C:\CLIMADOWN\Step2\TEMP\CNRM_RCP_85*
C:\CLIMADOWN\Step2\RR\ICHEC_hist	*C:\CLIMADOWN\Step2\TEMP\ICHEC_hist*
C:\CLIMADOWN\Step2\RR\ICHEC_RCP_26	*C:\CLIMADOWN\Step2\TEMP\ICHEC_RCP_26*
C:\CLIMADOWN\Step2\RR\ICHEC_RCP_45	*C:\CLIMADOWN\Step2\TEMP\ICHEC_RCP_45*
C:\CLIMADOWN\Step2\RR\ICHEC_RCP_85	*C:\CLIMADOWN\Step2\TEMP\ICHEC_RCP_85*
C:\CLIMADOWN\Step2\RR\IPSL_hist	*C:\CLIMADOWN\Step2\TEMP\IPSL_hist*
C:\CLIMADOWN\Step2\RR\IPSL_RCP_85	*C:\CLIMADOWN\Step2\TEMP\IPSL_RCP_85*
C:\CLIMADOWN\Step2\RR\MOHC_HADGEM2_hist	*C:\CLIMADOWN\Step2\TEMP\MOHC_HADGEM2_hist*
C:\CLIMADOWN\Step2\RR\MOHC_HADGEM2_RCP_45	*C:\CLIMADOWN\Step2\TEMP\MOHC_HADGEM2_RCP_45*
C:\CLIMADOWN\Step2\RR\MOHC_HADGEM2_RCP_85	*C:\CLIMADOWN\Step2\TEMP\MOHC_HADGEM2_RCP_85*
C:\CLIMADOWN\Step2\RR\MPI_ESM_hist	*C:\CLIMADOWN\Step2\TEMP\MPI_ESM_hist*
C:\CLIMADOWN\Step2\RR\MPI_ESM_RCP_85	*C:\CLIMADOWN\Step2\TEMP\MPI_ESM_RCP_85*

Table 3-6 Folders general classification

3.3.3 Step 3: Calculations

The follow section will explain how the data is organized to perform the calculations. There are mainly 3 different ways to compute future predictions:

- The procedure which calculates the delta change values regarding the model, scenario, location and period and applies it to the station data (3.1)
- Subset of scripts that apply the Engen-Skaugen bias correction method (Engen-Skaugen 2007) to the RCM_{hist} and RCM_{future} (3.2)
- The script that reads old scenarios data and transforms it to reach the same format (3.3).

It is clearly summarized in Figure 3-2.

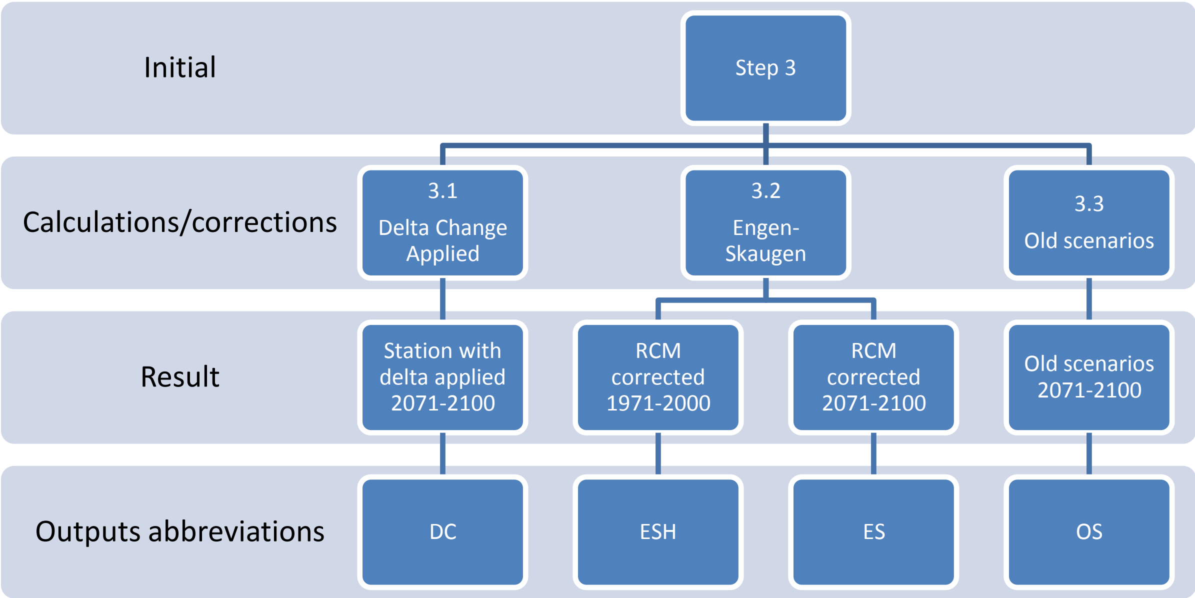


Figure 3-2 Scheme of the corrections made in step 3 and their output abbreviations

3.3.3.1 Delta change

This stage is composed of basically 2 main actions: firstly, the delta change values must be calculated (computed by the 3.1.1 script) in order to apply them after to the station data (script 3.1.2). Before going further, it is important to note that the delta change values are calculate differently regarding to if it is precipitation (calculated in %) or temperature (calculate in absolute values).

The script 3.1.1 compiles the daily values from the historical and each scenario for all the models and calculates the delta change for all the points of the RCM that fall into the selected area. This script was written by Netra Prasad Timalsina.

Name of the scripts	3.1.1.RCMDelta_CNRM_RR *(Note: the other scripts have the same name except little changes due to their characteristics)*
Number of scripts	10 (RR/TEMP and CNRM/ICHEC/IPSL/MOHC_HADGEM2/MPI_ESM)
Function	It takes the data from the Rdata files, and it calculates (for each model, scenario and RCM point of our catchment) the delta change value (DC) *(Note: the delta change value is computed differently according to precipitation or temperature)*
Input files	• Rdata files (*.Rdata): daily data for each model historical and scenarios
Input files location	It is extracted from the corresponding folder: *C:\CLIMADOWN\Step2* *C:\CLIMADOWN\Step3.1.1*
Output files	• Rdata files (*.Rdata): it saves all the delta change values for each model and scenario (for each point of the catchment and also a mean of all them) *(Note: It also generates files inside of the corresponding historical or scenario folder with the annual sum, mean monthly and mean monthly average that are not going to be used in this project)*
Output files location	*C:\CLIMADOWN\Step3.1.1\RR\All_DELTA* *C:\CLIMADOWN\Step3.1.1\TEMP\All_DELTA*

Table 3-7 Information about scripts 3.1.1

The formulas to calculate the delta change values are shown below:

Formula for the precipitation (RR)

$$\Delta p_j = \left(\frac{Model\ Scenario}{Model\ Historical}\right) 100$$

Equation 1 Delta change value precipitation

Where,

Δp_j = Delta change value precipitation (%)

$Model\ Scenario = mean\ monthly\ values\ for\ model, scenario\ in\ 2071 - 2100\ (mm)$

$Model\ Historical = mean\ monthly\ values\ for\ model\ historical\ in\ 1971 - 2000\ (mm)$

j = month j

Formula for the temperature (TEMP)

$$\Delta t_j = (Model\ Scenario\ ) - (Model\ Historical)$$

Equation 2 Delta change value temperature

Where,

Δt_j = Delta change value temperature (°C)

$Model\ Scenario = mean\ monthly\ values\ for\ model, scenario\ in\ 2071 - 2100$ (°C)

$Model\ Historical = mean\ monthly\ values\ for\ model\ historical\ in\ 1971 - 2000$ (°C)

j = month j

The script 3.1.2 applies the delta change values calculated in the previous script to the station data (1971-2000) for one point for all the models and scenarios. Further detailed inputs and outputs are found in Table 3-8.

Name of the scripts	3.1.2.AllModels_DeltaApplied_120205_RR *(Note: the other scripts have the same name except little changes due to their characteristics)*
Number of scripts	6 (RR/TEMP and 120205/120619/123165)
Function	It takes the delta change values and it applies them to the station data (DC) *(Note: the delta change value is computed differently according to precipitation or temperature)*
Input files	• Rdata files (*.Rdata): delta change values for all the RCM points for the model scenario • Station Data: daily data from the station selected
Input files location	The data from station: *C:\CLIMADOWN\StationData* The delta change values: *C:\CLIMADOWN\Step3.1.1\RR\All_DELTA* *C:\CLIMADOWN\Step3.1.1\TEMP\All_DELTA*
Output files	• CSV files (*.csv): it saves the daily values with delta change applied. *(Note: It is saved with the following name "code_DC_Data" where code can be (120205,120619 or 123165) and Data (RR or TEMP)*
Output files location	*C:\CLIMADOWN\Step4*

Table 3-8 Information about scripts 3.1.2

The following formulas are used to apply delta change values to the station data:

Formula for the precipitation (RR)

$$DCp_j = Station\ value\left(1 + \frac{\Delta p_j}{100}\right)$$

Equation 3 Delta change value precipitation applied

Where,

Δp_j = Delta change value precipitation (%)

$Station\ value = daily\ values\ in\ 1971 - 2000\ (mm)$

$DCp_j = Delta\ change\ applied\ daily\ values\ for\ model\ and\ scenario\ in\ 2071 - 2100\ (mm)$

j = month j

Formula for the temperature (TEMP)

$$DCt_j = (Station\ value) + (\Delta t_j)$$

Equation 4 Delta change value temperature applied

Where,

Δt_j = Delta change value temperature (°C)

$Station\ value = daily\ values\ in\ 1971 - 2000\ (°C)$

$DCt_j = Delta\ change\ applied\ daily\ values\ for\ model\ and\ scenario\ in\ 2071 - 2100\ (°C)$

j = month j

One example of each script, one for temperature and one for precipitation can be found in Appendix B.

3.3.3.2 Engen-Skaugen adjustment

In general sense, the aim of this step is to apply Engen-Skaugen bias correction on the RCM_{hist} and RCM_{future} as Torill Engen-Skaugen presents on her paper (Engen-Skaugen 2007). The method is for adjusting dynamically downscaled precipitation and temperature scenarios representing specific sites. This method has been modeled and performed to make the necessary corrections to the RCM historical as well as the RCM future for each model and scenario.

The main details of the set of script that apply the Engen-Skaugen method and reach the common format for further comparison are explained in the Table 3-9.

Name of the scripts	3.2.EgenSkaugen_120205__RR *(Note: the other scripts have the same name except little changes due to their characteristics)*
Number of scripts	12 (RR/TEMP, hist, 120205/120619/123165)
Function	It takes the data from the station and the RCM values and it applies (for each model and scenario) the Engen-Skaugen method correction. *(Note: the delta changed value is computed differently according to precipitation or temperature)*
Input files	• Daily data from the corresponding station • Rdata files (*.Rdata): daily data for each model historical and scenarios
Input files location	It is extract from the corresponding folder: *C:\CLIMADOWN\StationData* *C:\CLIMADOWN\Step3.1.1*
Output files	• CSV file (*.csv) It returns daily data corrected with the Engen-Skaugen method.
Output files location	*C:\CLIMADOWN\Step4*

Table 3-9 Information about scripts 3.2

It is important to note that adjustment is performed differently if it is precipitation data or temperature values. One example of script of precipitation and temperature can be found in Appendix C.

a. Precipitation adjustment

The study is carried out using historical daily data from 1971-2000 of the RCMs and station data. The RCM daily values for the future 2071-2100 are also necessary to perform the calculations. The method suggested by (Engen-Skaugen 2007) is applied as below:

Daily precipitation values are normalized and standardized for the scenario period (in the study 2071-2100) to obtain a residual containing variability of the daily precipitation data series (Eq. 5):

$$\frac{P_{RCMJ1sc,ijk} - m_{P,RCMJ1sc,j}}{\sigma_{P,RCMJ1sc,j}} = \varepsilon_{p,sc,ijk}$$

Equation 5 Residual containing the variability of the daily precipitation data series

Where $P_{RCMJ1sc,ijk}$ is the daily precipitation at day number i in month j and scenario period sc, $m_{P,RCMJ1sc,j}$ is the mean monthly precipitation value in month j in the scenario period sc., $\sigma_{P,RCMJ1sc,j}$ is the standard deviation based on daily values for month j in the scenario period sc, and $\varepsilon_{p,sc,ijk}$ is the residual at day i in month j in year k in the scenario period sc.

The method assumes that the monthly RCM error variability in the scenario period is the same as for the control period γ_{Pj}:

$$\gamma_{Pj} = \frac{\sigma_{P,obs,j}}{\sigma_{P,RCMJ1ctrl,j}}$$

Equation 6 Formula to calculate γ_{Pj}

$$\hat{\sigma}_{P,sc,j} = \gamma_{Pj}\sigma_{P,sc,j}$$

Equation 7 Formula to calculate $\hat{\sigma}_{P,sc,j}$

Where $\sigma_{P,obs,j}$ is monthly (j) standard deviation (σ) based on observed daily station values (obs) within the control period. $\sigma_{P,RCMJ1ctrl,j}$ is monthly (j) standard deviation() based on the RCM daily values (RCMJ1) within the control period.

Month	γ_{Pj}	$\sigma_{P,obs,j}$	$\sigma_{P,RCMJ1ctrl,j}$	$\sigma_{P,sc,j}$	$\hat{\sigma}_{P,sc,j}$	β_{Pj}
Jan	1.224	8.408	6.867	8.588	10.514	1.231
Feb	0.997	7.499	7.520	8.778	8.753	1.176
Mar	1.223	7.802	6.378	6.675	8.166	1.054
Apr	0.933	6.152	6.595	6.475	6.040	1.094
May	1.163	7.430	6.390	7.133	8.293	1.013
Jun	1.314	7.975	6.067	7.710	10.134	1.198
Jul	1.358	9.657	7.110	7.936	10.778	1.067
Aug	1.088	10.595	9.737	9.517	10.356	0.975
Sep	1.199	11.263	9.397	9.743	11.679	0.961
Oct	1.091	11.192	10.255	8.904	9.718	0.794
Nov	1.031	10.072	9.770	9.089	9.370	0.948
Des	1.268	8.895	7.013	8.926	11.321	1.233

Table 3-10 Example of the main parameters obtained on the empirical adjustment

β_{Pj} is the ratio between the scenario mean monthly (j) sums $m_{P,RCMJ1sc,j}$ and control mean monthly (j) sums ($m_{P,RCMJ1ctrl,j}$) based on daily values:

$$\beta_{Pj} = \frac{m_{P,RCMJ1sc,j}}{m_{P,RCMJ1ctrl,j}}$$

Equation 8 Formula to calculate β_{Pj}

Adjusted daily precipitation is obtained by multiplying daily residual values (Eq. 5) with the adjusted standard deviation for the scenario period (Eq. 7). Mean monthly values of daily precipitation based on observations within the control period multiplied with β_{Pj} is added.

The mean differences between mean monthly values in a scenario period and a control period are maintained:

$$P_{RCMJ2sc,ijk} = \varepsilon_{p,sc,ijk}\hat{\sigma}_{P,sc,j} + m_{P,obs,j}\beta_{Pj}$$

Equation 9 Formula to calculate adjusted precipitation $P_{RCMJ2sc,ijk}$ (a)

$$P_{RCMJ2sc,ijk} = \left(P_{sc,ijk} - m_{P,sc,j}\right)\gamma_{Pj} + m_{P,obs,j}\beta_{Pj}$$

Equation 10 Formula to calculate adjusted precipitation $P_{RCMJ2sc,ijk}$ (b)

Where $P_{RCMJ2sc,ijk}$ is the adjusted precipitation for day i in month j for the scenario period sc.

If $m_{P,sc,j} > m_{P,obs,j}$ scenario values of daily precipitation $P_{RCMJ2sc,ijk}$ will be negative. Negative values are set to 0.0mm, thus, the mean monthly precipitation sum and standard deviation based on daily precipitation will be too large compared to the statistical moments based on observations. The equations 5-10 are therefore performed all over again in the new dataset ($P_{RCMJ2sc,ijk}$). The iteration is repeated until the mean value and the standard deviation is satisfactorily reproduced. It is performed all over again until the number of negative values is less than the 10% (in this study this limit is fixed in 219).

b. Temperature

The temperature values interpolated from the regional climate model are sometimes not very well estimated because of the altitude difference. To correct the daily temperatures due to altitude biases a temperature lapse rate which closely matches the averages observed lapse rate in the troposphere (-0.65°C/100m) (Houghton 1985) is used:

$$T_{RCMJ1sc,ijk} = T_{RCMsc,ijk} - 0.65\frac{\Delta h}{100}$$

Equation 11 Formula to correct altitude biases

Where $T_{RCMsc,ijk}$ is interpolated temperature values from the RCM, $T_{RCMJ1sc,ijk}$ is the height corrected temperature values and Δh is the height difference.

The average RCM height is assumed to be 5.75m according to CORDEX archive design. Hence, the final Δh value for each station is presented below:

Name of station	$h\ (m)$	$\Delta h\ (m)$
Sirdal	500	494.25
Lista Fyr	14	8.25
Kjevik	12	6.25

Table 3-11 Stations heights (h) and height increments (**Δh**)

Equations similar to (Eqs. 5-10) are performed for temperature as shown in (Eqs. 12-17), respectively. Daily data obtained of (Eq. 11) is normalized and standardized (Eq. 12):

$$\frac{T_{RCMJ1sc,ijk} - m_{T,RCMJ1sc,j}}{\sigma_{T,RCMJ1sc,j}} = \varepsilon_{T,sc,ijk}$$

Equation 12 Residual containing the variability of the daily temperature data series

Where $m_{T,RCMJ1sc,j}$ is the mean monthly temperature value in month j in the scenario period sc, $\sigma_{T,RCMJ1sc,j}$ is the standard deviation based on daily values for month j in the scenario period sc, and $\varepsilon_{T,sc,ijk}$ is the residual at day i in month j in year k in the scenario period sc.

$$\gamma_{Tj} = \frac{\sigma_{T,obs,j}}{\sigma_{T,RCMJ1ctrl,j}}$$

Equation 13 Formula to calculate γ_{Tj}

$$\hat{\sigma}_{T,sc,j} = \gamma_{Tj}\sigma_{T,sc,j}$$

Equation 14 Formula to calculate $\hat{\sigma}_{T,sc,j}$

The method force the modelled data to satisfactorily reproduce mean monthly values in the control period obtained by RCM by using the absolute change between the scenario mean monthly values ($m_{T,RCMJ1sc,j}$) and control mean monthly values ($m_{T,RCMJ1ctrl,j}$), β_{Tj}:

$$\beta_{Tj} = m_{T,RCMJ1sc,j} - m_{T,RCMJ1ctrl,j}$$

Equation 15 Formula to calculate β_{Tj}

Finally, adjusted daily temperatures are calculated by multiplying daily residuals (Eq. 12) with adjusted standard deviation for the scenario period (Eq. 14) and add the observed mean value and β_{Tj}:

$$T_{RCMJ2sc,ijk} = \varepsilon_{T,sc,ijk}\widehat{\sigma}_{T,sc,j} + \left(m_{T,obs,j} + \beta_{Tj}\right)$$

Equation 16 Formula to calculate adjusted temperature $T_{RCMJ2sc,ijk}$ (a)

$$T_{RCMJ2sc,ijk} = \left(T_{sc,ijk} - m_{T,sc,j}\right)\gamma_{Tj} + \left(m_{T,obs,j} + \beta_{Tj}\right)$$

Equation 17 Formula to calculate adjusted temperature $T_{RCMJ2sc,ijk}$ (b)

Mean value and variability for the control period is then reliably estimated and the mean differences in mean value and standard deviation as obtained by RCM is maintained.

3.3.3.3 Old scenarios

Certainly, it is interesting to compare how the system responds to the new scenarios and how old scenarios correspond with the new ones. Therefore, data from the old scenarios are downloaded from the “Norwegian service center for climate modeling” (*NoSerC*). Only data from the A2 and B2 old scenarios is downloaded due to the availability regarding the location of the points and the time period that are compared in the thesis.

The script “*3.3.All points_Old_Scenarios_Data_All_(RR&TEMP)*” collects the data and transforms it into the common format for later comparison. The script details are presented in Table 3-12 and it can be found in the Appendix D.

Name of the scripts	3.3.All points_Old_Scenarios_Data_All_(RR&TEMP)
Number of scripts	1
Function	It takes the data from the old scenarios and transforms it to the common format
Input files	• CSV file (*.csv) Daily data from the old scenarios
Input files location	It is extract from the following folder: *C:\\CLIMADOWN\\OldScenariosData*
Output files	• CSV file (*.csv) It returns daily data of all scenarios in the right format
Output files location	*C:\CLIMADOWN\Step4*

Table 3-12 Information about the script 3.3

3.3.4 Step 4: Comparison

At this stage, all the information is organized, classified regarding its characteristics and has the same common format for a comparison.

The comparison carried out in this step analyzes the differences between the following 5 outputs as shown in Figure 3-3. Station data with Delta Change applied (DC), RCM_{hist} bias corrected with Engen-Skaugen method (ESH), RCM_{future} bias corrected with Engen-Skaugen method (ES), Old Scenarios (OS) and actual observation data from the station (OBS).

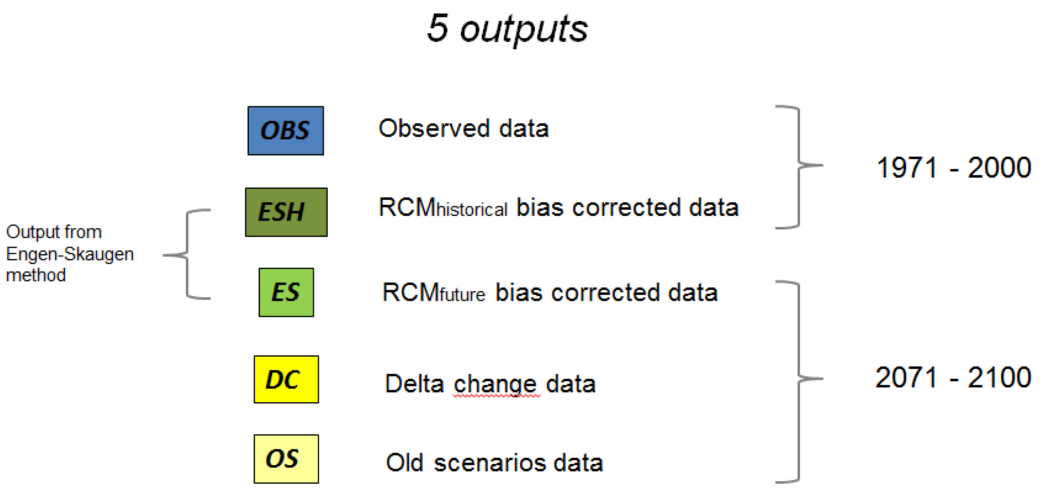


Figure 3-3 Outputs compared in the step 4. ESH and ES are the output from the bias correction. All subsets of data are daily. The period is shown in the right side of the figure.

Comparisons between the outputs that belong to the same period are performed and main differences are assessed. Although RCM_{hist} bias corrected with Engen-Skaugen method (ESH) and RCM_{future} bias corrected with Engen-Skaugen method (ES) do not belong in the same period, they are compared to appreciate the differences regarding temperature and precipitation between them with the correspondent discussion and assessment.

One script performed all the comparisons for each station or location. Thus, 3 different scripts are written. One example of the script of comparison can be found in the Appendix F.

3.4 Results and discussion

The follow section will show the several comparisons assessed where temperatures and precipitations are examined.

The five main comparisons are assessed below:

1. RCM_{hist} bias corrected and RCM_{future} bias corrected (ESH-ES)
2. RCM_{future} bias corrected and Old Scenarios (ES-OS)
3. RCM_{hist} bias corrected and Observed data from the station (ESH-OBS)
4. Delta change and Old scenarios (DC-OS)
5. Delta change and RCM_{future} bias corrected (DC-ES)

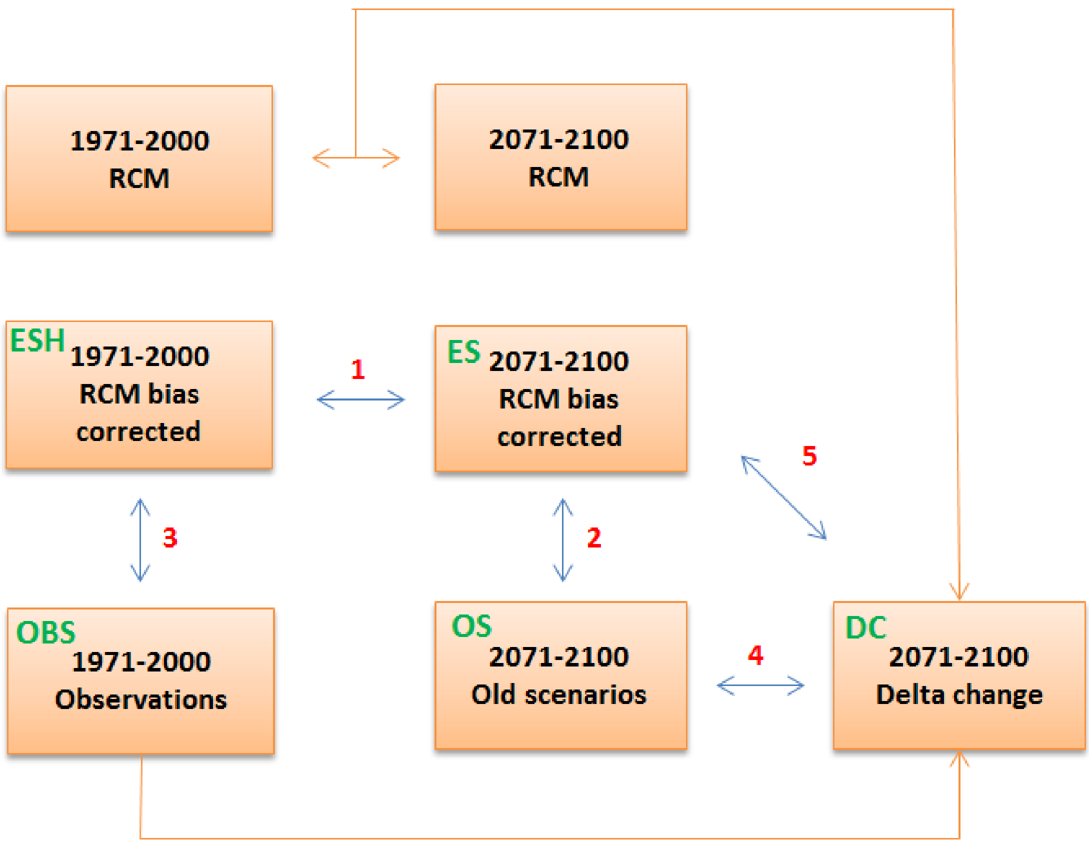


Figure 3-4 Scheme of the main subsets data outputs. Blue arrows indicate a comparison and numbers in red match with the comparison number. Orange arrows that converge to DC mean the data used to calculate it. Finally, green names correspond to the abbreviations presented in 3.3.3 section.

3.4.1 Comparison between RCM_{hist} bias corrected and RCM_{future} bias corrected (ESH-ES)

The follow section will show the results from the comparison between RCM_{hist} and RCM_{future}, both bias corrected, where it is possible to notice the future changes due to the predictions compared with the historical values. For each station, the monthly mean values of RCM_{hist} and RCM_{future} are shown (Figure 3-5).

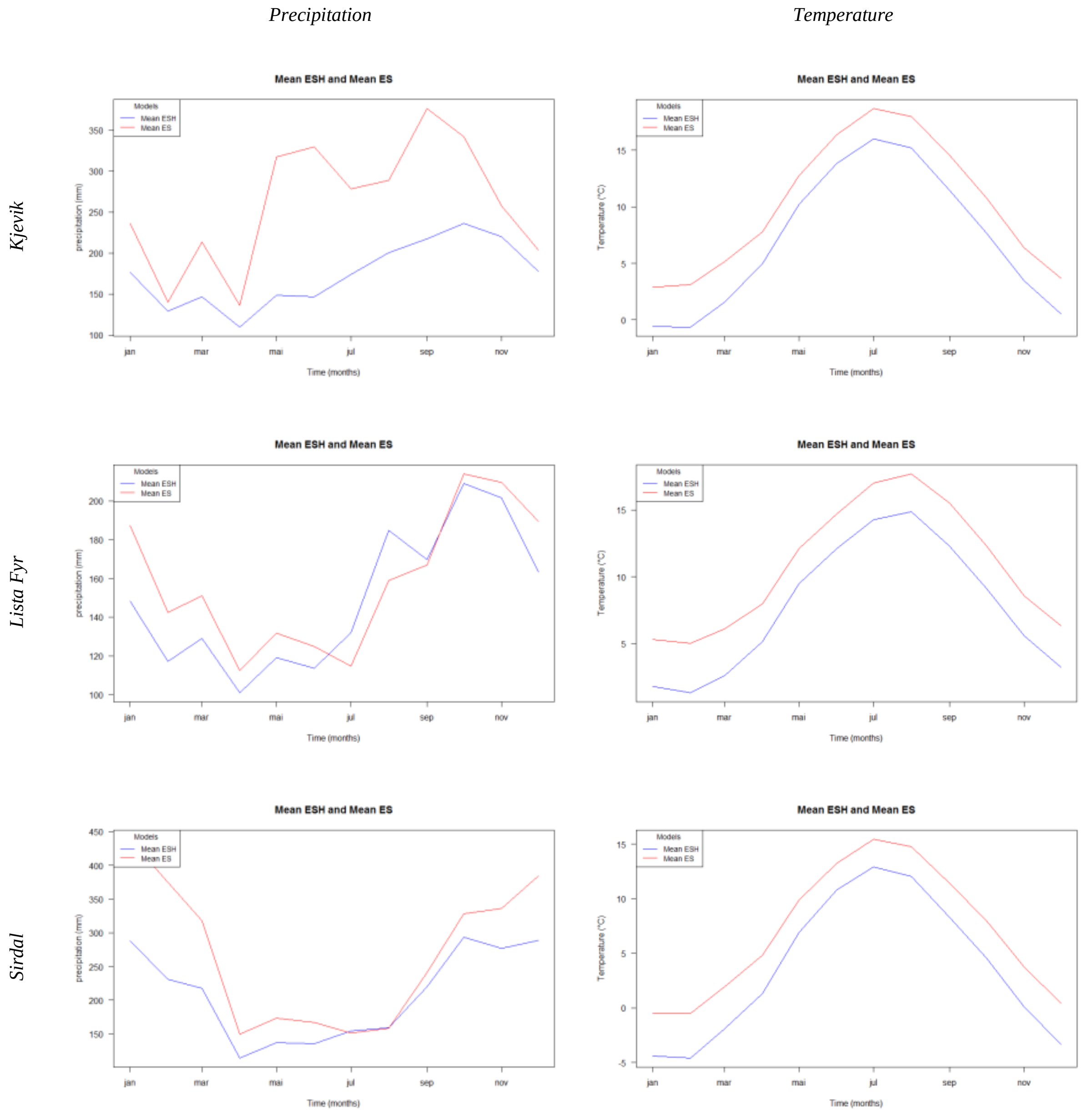


Figure 3-5 Graphs of the monthly mean precipitation and daily mean temperature of RCM_{hist} bias corrected and RCM_{future} bias corrected according to each station

Although precipitation values are oscilantly widely, in general RCM_{future} bias corrected values indicate a higher precipitation in comparison with the RCM_{hist} bias corrected results. While in Sirdal and Lista Fyr, present a slight less increase in precipitation, in the Kjevik case, the increment is much remarkable. It is also worthwhile mentioning that Kjevik station shows a significant increase especially in summer and in autumn. On the other side, the other 2 stations indicate an increase of precipitation mainly in winter and beginning of spring.

All stations perform a clearly increase in temperature with a slightly higher increase from December to February in all cases. In the next page, an overview of all models and scenarios together, graphs separated by model are presented for the case of station Sirdal.

Sirdal

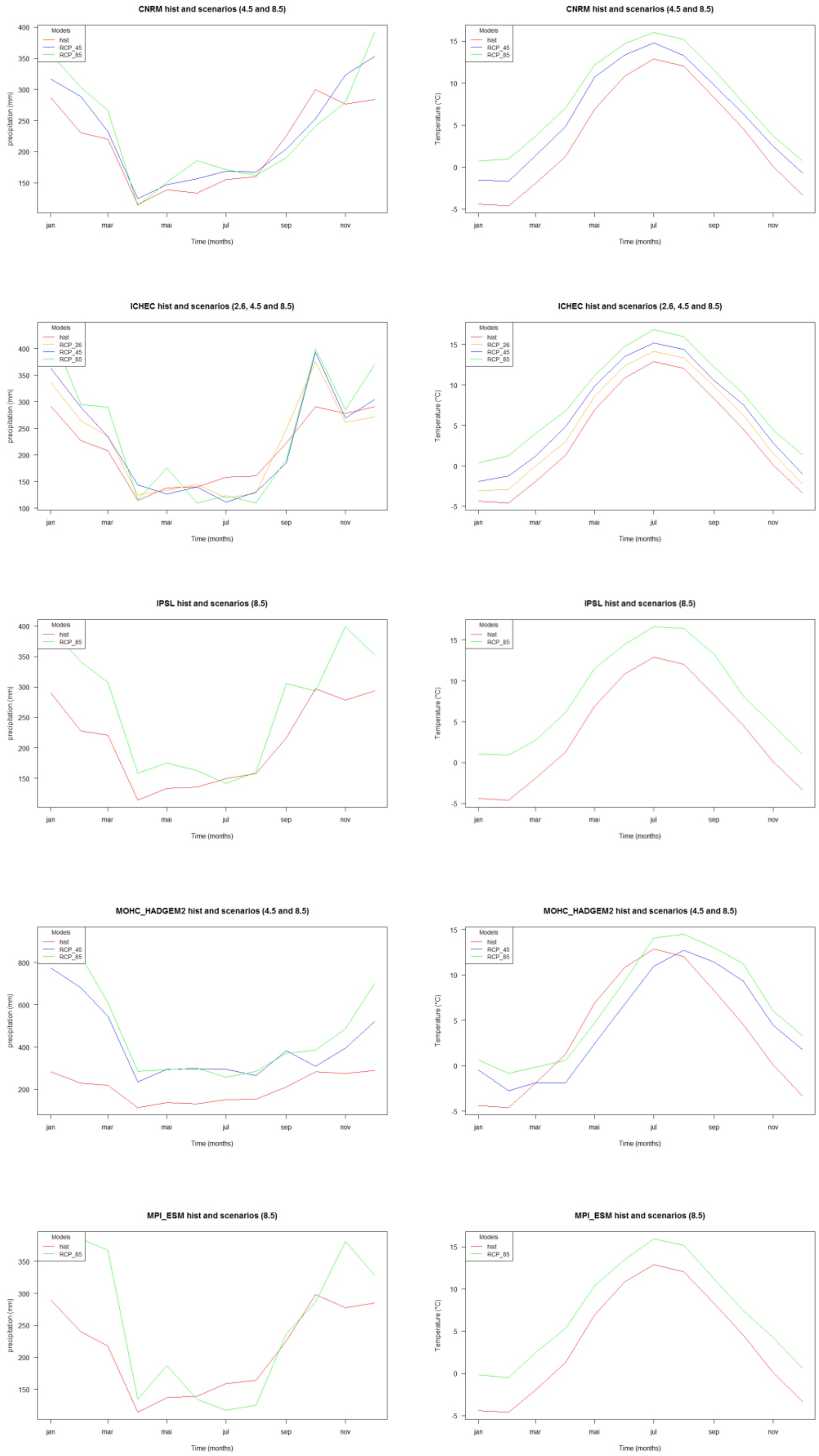


Figure 3-6 RCM$_{hist}$ bias corrected and RCM$_{future}$ bias corrected for all the models and scenarios in Sirdal station for precipitation (left) and temperature (right).

Generally, an increasing precipitation is observed in the future scenarios, and significantly more from November to March. On the other side, ICHEC model predicts a high peak of rainfall in October.

Judging by the Figure 3-6, it is noticed that the model and the scenarios influence to the final outcomes. Furthermore, it is clearly noticed that future temperature are higher for all models and scenarios and particularly increases in the following order: historical, scenarios RCP 2.6, scenario RCP 4.5 and scenario RCP 8.5.

It is worthwhile to notice that the model HADGEM2 scenario RCP 4.5 presents a strange behavior not only in Sirdal but also in Kjevik and Lista Fyr as can be observed in the Appendix E. Therefore, it is not considered in the future comparisons.

Lastly, it is important to mention that in general, temperature results are clearer than rainfall values and present less spread.

3.4.2 Comparison between and Old Scenarios (ES-OS)

The follow section will illustrate the results obtained from the relation between future and old scenarios.

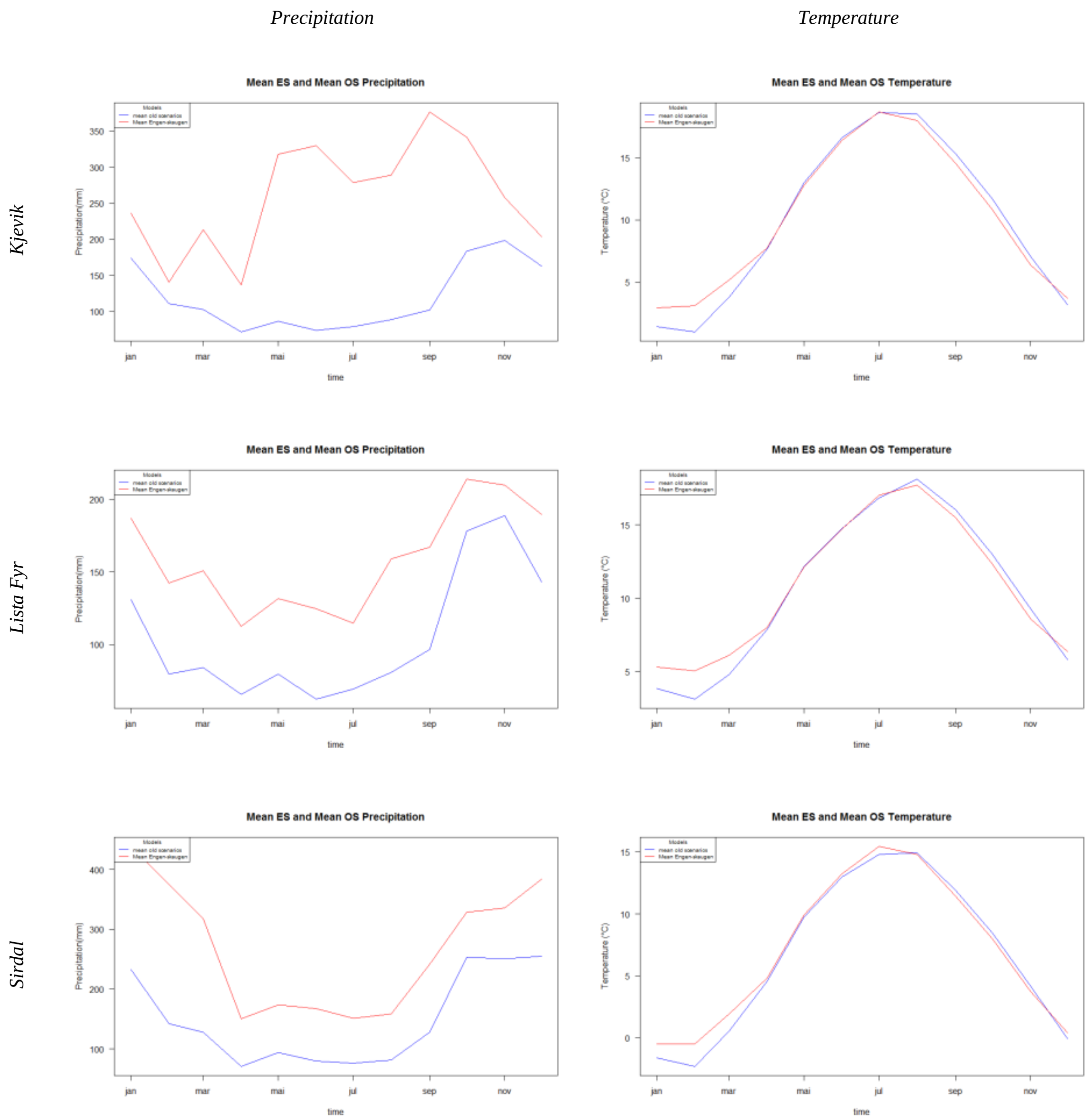


Figure 3-7 Graphs with the mean monthly precipitation values and daily mean temperature of old scenarios (blue) and RCM_{future} bias corrected (red) of each station

In all cases, RCM_{future} bias corrected present greater values in comparison with old models. Substantial differences can be found between locations or stations, especially in Kjevik station where a significant peak is predicted by the Engen-Skaugen method applied in RCM_{future}.

In contrast, RCM_{future} bias corrected and old models show a satisfactory agreement and all present very similar values throughout the year. It is interesting the fact that all locations simulate the same slightly increase in January and February, though it is meager.

In the appendix E the same graphs of precipitation and temperature according to each model and scenario are attached.

To sum up, RCM_{future} bias corrected and old models are comparable as regards the temperature but not in the case of rainfall, where the old models present a significant less precipitation.

3.4.3 Comparison between RCM_{hist} bias corrected and Observed data from the station (ESH-OBS)

It is also interesting to compare the RCM_{hist} bias corrected and actual observations in the stations for the periods 1971-2000 to see the correspondence in the historical period. In the case of Lista Fyr and Kjevik observation data is available for the mentioned period but, Sirdal observations data is only available from 1974 to 2000, so this period is taken into account to compute the values in this last location.

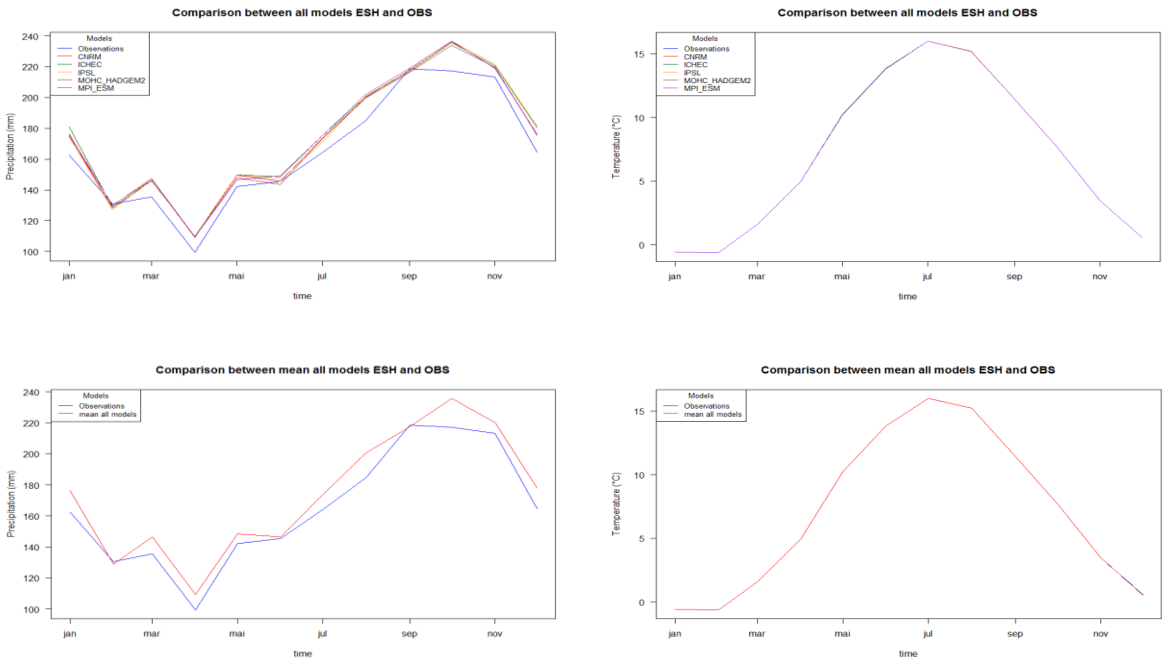


Figure 3-8 Graphs of Kjevik mean monthly precipitation (left) and mean monthly temperature (right) for RCM_{hist} bias corrected and observed data. On the upper part, they are categorized by models and, on the lower part, the mean of all the models is compared to the observed data.

In Kjevik station, a great agreement is illustrated in precipitation results and an excellent correspondence in temperature values. Thus, Engen-Skaugen bias correction method works very well with the RCM_{hist} models both for precipitation and temperature. Similar results are obtained with the Lista Fyr and Sirdal as shown in the following graphs.

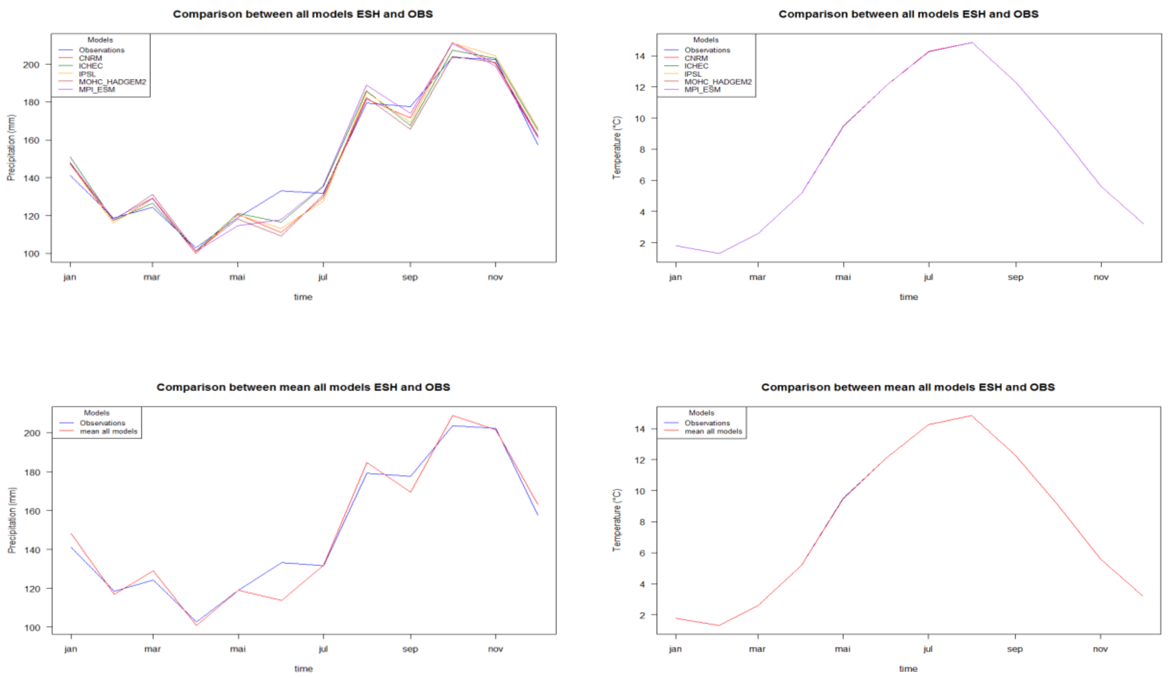


Figure 3-9 Graphs of Lista Fyr mean monthly precipitation (left) and mean monthly temperature (right) for RCM_{hist} bias corrected and observed data.

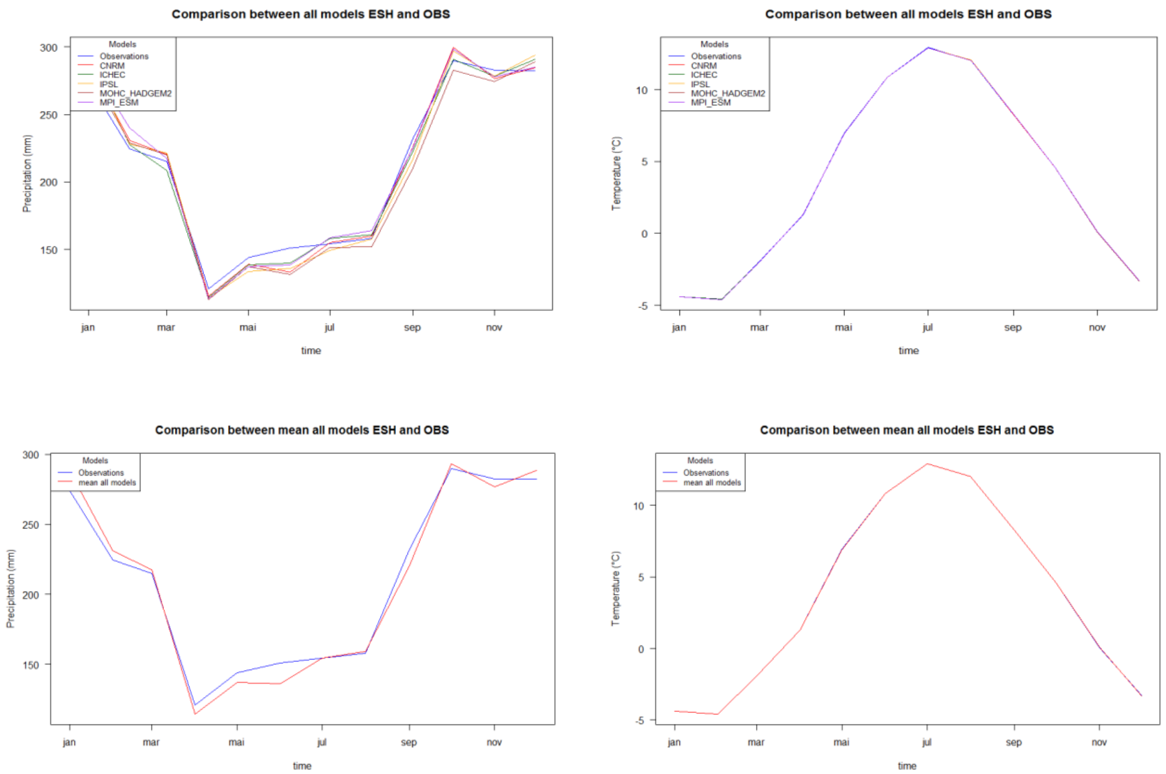


Figure 3-10 Graphs of Sirdal mean monthly precipitation (left) and mean monthly temperature (right) for RCM_{hist} bias corrected and observed data.

3.4.4 Comparison between Delta change and Old scenarios (DC-OS)

The follow section presents a comparison between delta change values applied on the station data and the old scenarios downloaded.

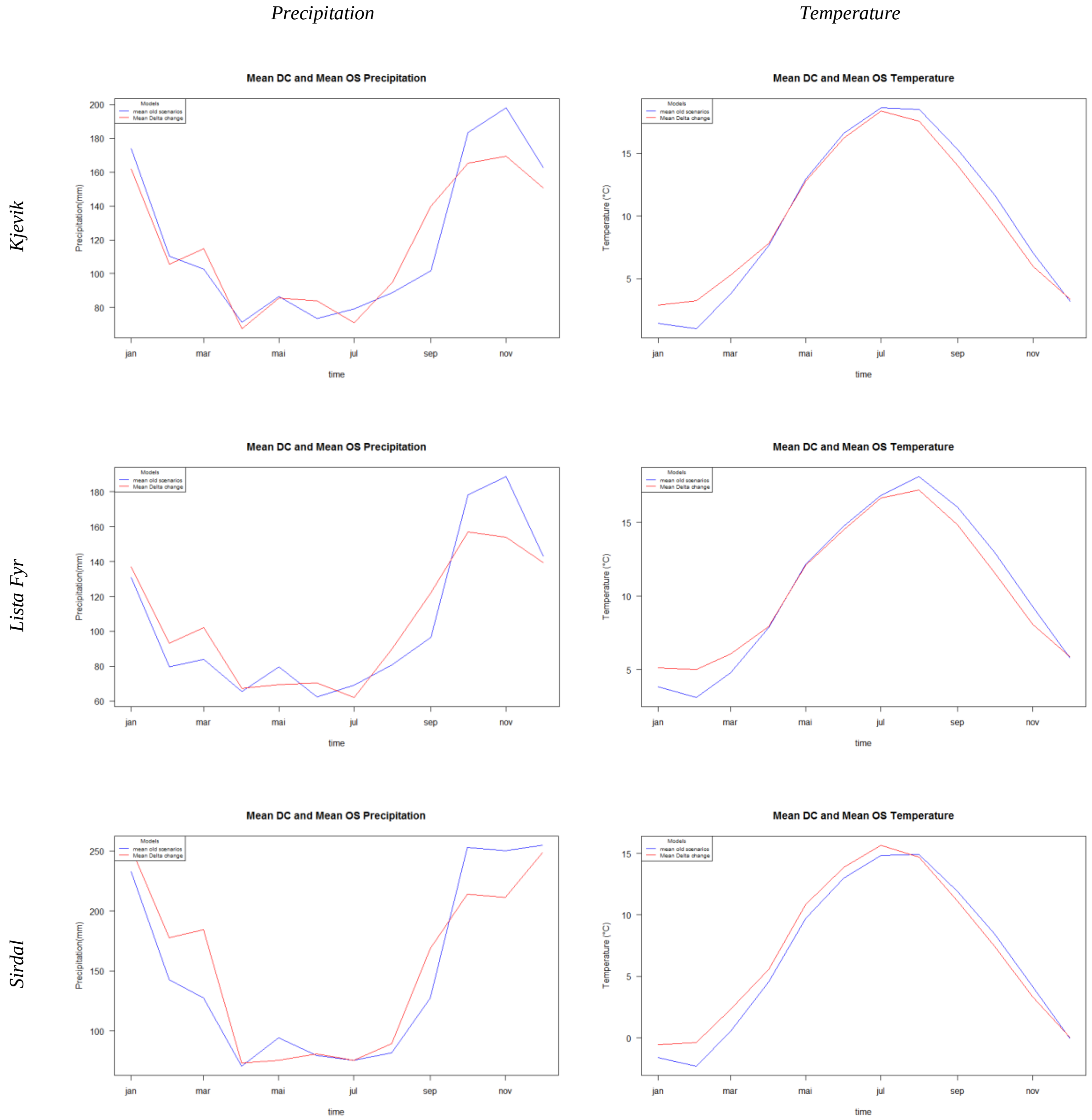


Figure 3-11 Comparison between Delta change and Old scenarios for precipitation (left) and temperature (right) categorized by stations

Great correspondences are observed between delta change values and old scenarios in both, temperature and precipitation, for all the stations. In general, delta change precipitation values show a slight rise in October and November while a decrease is presented in February and March.

The graphs where the same comparison is performed categorized by models are attached in the appendix E.

3.4.5 Comparison between Delta change and RCM$_{future}$ bias corrected (DC-ES)

The follow section asses the differences between Delta change and RCM$_{future}$ bias corrected in order to study the differences between them. It is a worthy comparison as both of them have been based on the new scenarios (AR5).

Delta change and RCM$_{future}$ bias corrected graphs for Sirdal show that precipitation values of ES are higher than DC simulations. Temperature values perform a good correspondence.

Sirdal

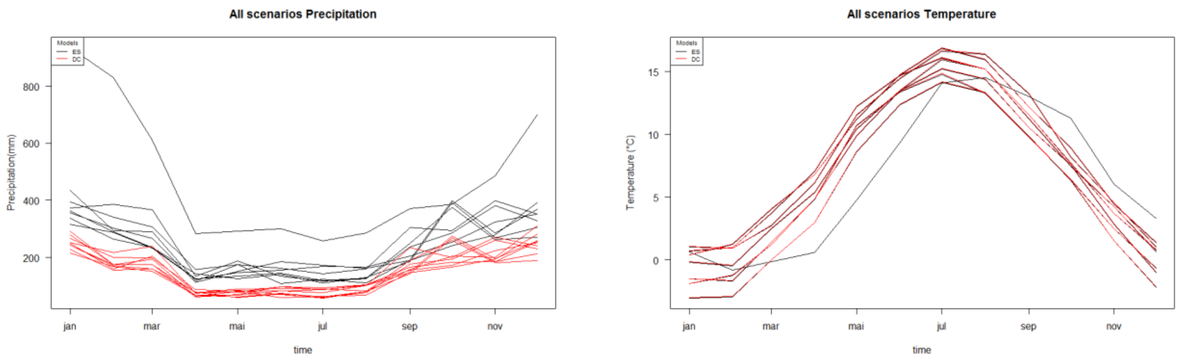


Figure 3-12 Comparison between Delta change and RCM$_{future}$ bias corrected for precipitation (left) and temperature (right) for Sirdal station

The same graphs for the rest of the stations can be found in the appendix E.

In order to have an overview, following graphs show the relation between mean monthly delta change values and mean of RCM$_{future}$ bias corrected for precipitation and temperature for each station.

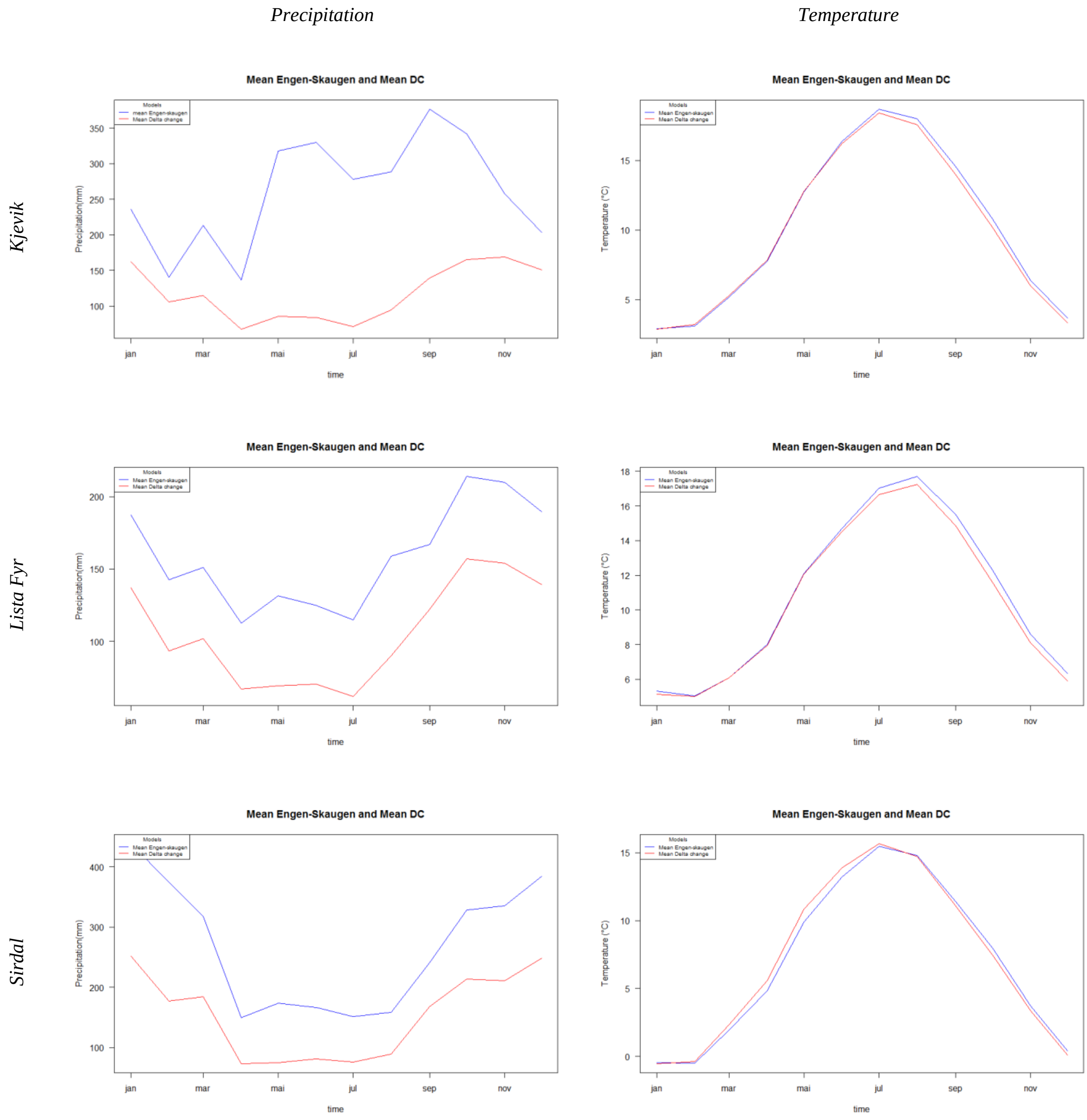


Figure 3-13 Comparison between Delta change and RCM$_{future}$ bias corrected for precipitation (left) and temperature (right) categorized by stations

In all stations RCM$_{future}$ bias corrected with the Engen-Skaugen method suggest a substantial increase of rainfall throughout the year and a great agreement is performed in temperature values.

3.5 Conclusions

Apart from the conclusions explained on each of the sections 3.4.1-3.4.5, after all the comparisons performed other conclusions that are worth to explain are explained below.

Temperature predictions for period 2071-2100 present similar results; either they come from Delta change calculations, Old scenarios or RCM_{future} bias corrected. Besides that, results obtained by applying the Engen-Skaugen bias correction to the RCM_{hist} have shown an exceptional agreement with the observed data. Thus, it can be concluded that no significant differences are appreciable between methods regarding temperatures. An increase of temperatures between 2 and 4 ºC is predicted according to the comparison between RCM_{future} bias corrected and RCM_{hist} bias corrected (Figure 3-5)

On the contrary, less correspondence is observed in precipitation data. Although Old scenarios and Delta change values show good agreement, the greater difference is found between RCM_{future} bias corrected and them. RCM_{future} bias corrected results suggest a considerable increase on the precipitation throughout the year. This results lead to the conclusion that mixing the Old scenarios and new ones on RCM_{future} bias corrected with the Engen-Skaugen method has to be taken into consideration very carefully.

Another aspect to take into account is the amount of data available from old scenarios compared to the new scenarios in the study. While only 2 scenarios were examined from the old scenarios, there were 9 scenarios corresponding to the new scenarios. The major number of scenarios the more reliable the average results are. However, that is the current data available and the study has to deal with this issue.

In the end of the section 3, data must be selected for the next step as an input for the HBV model. The station selected is Kjevik because it is the closest station to the catchment selected (Mandalselva) and to Myglevatn, where the calibration of the model is computed. Therefore, the data selected is the subset of delta change values (DC) in view of the fact that RCM_{future} bias corrected present significant differences as observed in the comparisons.

4 HBV model

4.1 Introduction

The HBV or *Hydrologika Byråans Vattenbalansavdelning* is a conceptual model of catchment hydrology which is used for runoff simulation, inflow and flood forecasting. This model computes the inputs (temperatures, precipitation and potential evapotranspiration) and calculates the following values: snow accumulation, actual evapotranspiration, snow melt, storage in soil moisture and groundwater and runoff from catchment (Killigtveit 1995).

The HVB model also requires the catchment's properties to perform and give the outputs mentioned before. The model is run with precipitation and temperatures time series on daily time step. It is a mathematical model of the hydrological processes in a catchment. The general equation can be described as:

$$P - E - Q = \frac{d}{dt}[SP + SM + UZ + LZ + lakes]$$

Where,

P: precipitation

E: evapotranspiration

Q: runoff

SP: snow pack

SM: soil moisture

UZ: upper groundwater zone

LZ: lower groundwater zone

Lakes: lake volume

The HBV model is to some extent a linear model regarding that most of the expressions in the model are linear. The model is extensively used for hydropower planning and operation. It can have many different applications such as runoff and flood forecasting, to determine the effects of changes in the catchment or to study the effects of climate change.

The version of the model used is Pine HBV Version 1.0 developed by Trond Rinde (Dr. Ing and Hydro informatics in NTNU), (Rinde 2003).

4.2 HBV structure

The structure of the HBV model is based on the hydrological cycle. The four main storage components are: snow, soil moisture, upper zone and lower zone. The result of the calculation of the models is the storage in each component based on the inputs (temperatures, precipitation and potential evapotranspiration) in relation with the catchment parameters. The final output of the model is the runoff from the catchment but Pine HBV allows the user to visualize other characteristics such as the snowpack and snowmelt.

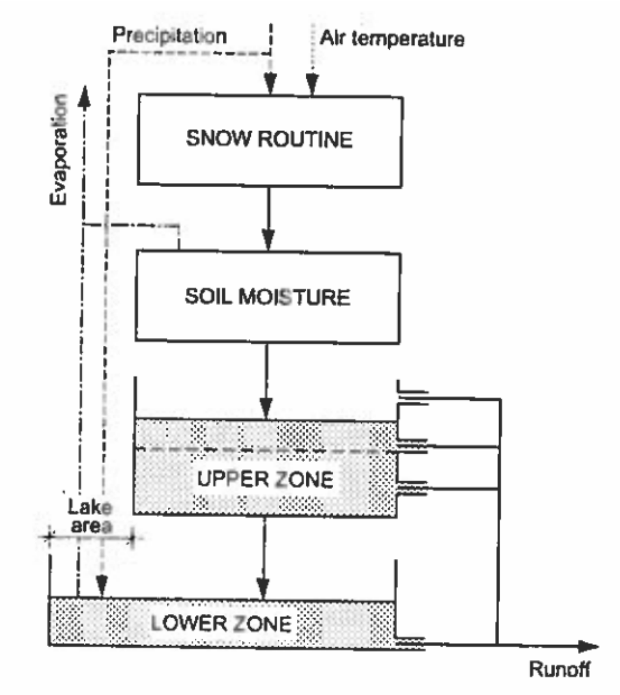


Figure 4-1 Main structure of HBV model

4.2.1 The snow routine

The snowmelt routine is computed with a degree-day approach. This factor is found according to the air temperature and a water capacity factor that delays the runoff. It is assumed that the snow pack hold the water as long as it does not exceed a certain fraction of snow. In addition, if the temperature decreases below the threshold temperature, this water refreezes (Figure 4-2).

The catchment is divided into elevation levels due to the elevation curve. At each zone, the model computes air temperature, amount of precipitation, precipitation type, snow melt or refreezing due to air temperature and temperature lapse rate. Hence, the structure of the snow routine is now distributed.

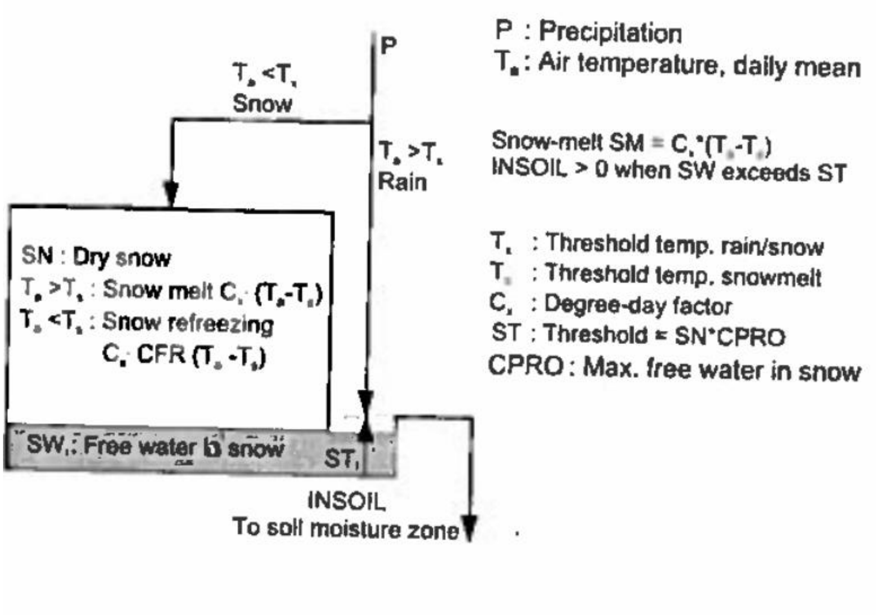


Figure 4-2 Snow routine in the HBV model

4.2.2 The soil moisture routine

The soil moisture routine receives rainfall and snow melt as input from the snow routine and computes the storage of water in soil moisture, actual evapotranspiration and the net runoff generating precipitation as output to the runoff response routine (Figure 4-3).

It is based on 2 simple equations based on 3 empirical parameters: β, FC and LP.

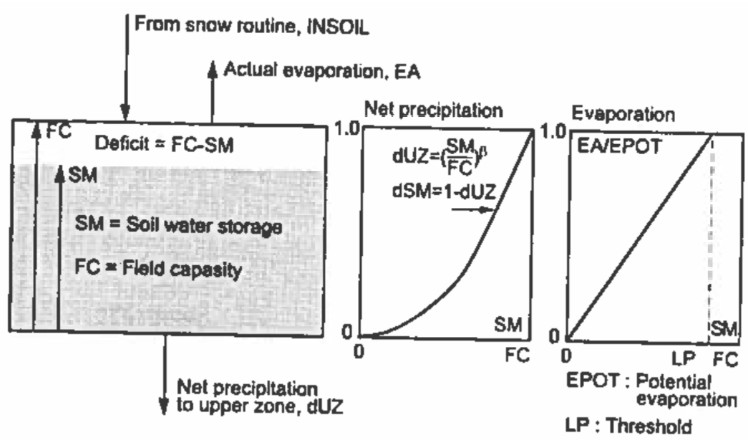


Figure 4-3 Soil moisture routine in the HBV model

The parameter β controls the contribution to the runoff response routine. LP is a parameter representing the soil moisture value below which actual evaporation is impeded. The parameter LP is a fraction of FC. These three parameters must be determined at the end of the calibration. If the rainfall or the snow melt is higher than the infiltration capacity, it is transferred directly to the run-off response.

4.2.3 The runoff response routine

The runoff response routine receives the net precipitation produced in the soil moisture routine and transforms it into runoff. The runoff response consists of two linear reservoirs: upper zone and lower zone, arranged as shown in the Figure 4-4. The effect of direct precipitation on and evaporation from rivers and lakes in the catchment is also included.

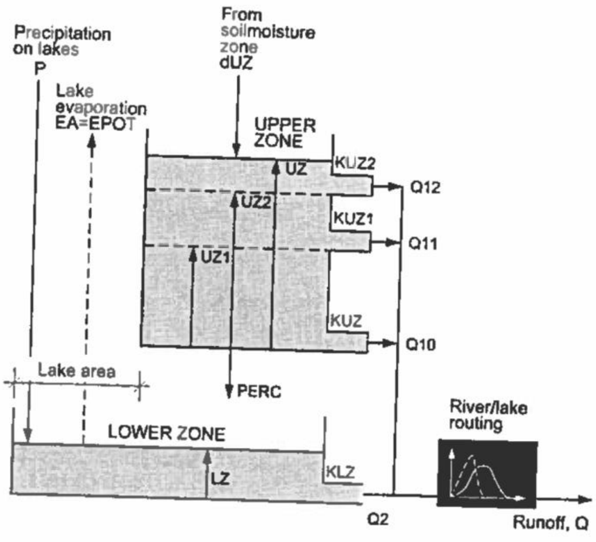


Figure 4-4 Runoff response routine in the HBV model

The upper zone consists of the quick runoff components such as the overland flow, the groundwater drained through more superficial channels, the runoff delay and timing. On the other hand, the lower zone represents the storage of water in deep groundwater and lakes, as well as the runoff delay and timing. The lower zone also computes the slow runoff from the groundwater and lakes, which is called base flow.

4.3 Model calibration

In general sense, the goal of the calibration of the HBV model is to determine the set of free parameters in model in order to the best correspondence between the observed and simulated runoff.

The main indicator that proves that the model is well calibrated is the function Nash-Sutcliffe Efficiency (R^2). Its formula is below:

$$R^2 = \frac{\sum(Q_0 - \bar{Q}_0)^2 - \sum(Q_s - \bar{Q}_0)^2}{(Q_0 - \bar{Q}_0)^2}$$

Where,

$Q_0 = observed\ runoff$

$\bar{Q}_0 = Average\ runoff$

$Q_s = simulated\ runoff$

This parameter can take values from 0 to 1 and it gives an idea of which percentage of the observation is explained by the simulated data. An R^2 value equals to 1 means that the simulation explains completely the observed data.

However, the R^2 parameter is not the only thing to take into account. Other results to examine are the accumulated runoff throughout the time period and also the accumulated difference that should not maintain a tendency. It is important to check if the simulation runoff follows the same patterns as the observed runoff. Floods and peaks of the time period must be verified.

As the data available for the observed period is from 1971-2000, the model calibration is carried out based on the data for the period 1995-2000, according to the hydrological year (01.09.1995 to 31.08.2000). It is important that the calibration period includes a variety of hydrological events. Then, the set of parameters obtained would be checked for other periods within the observed data periods.

For the calibration of the Pine HBV model the data of river flow of Myglevatn has been computed. The data from the catchment has been extract from the Norwegian Water Resources and Energy Directorate (NVE). The precipitation and temperatures values are taken from the Kjevik station (Figure 4-5)

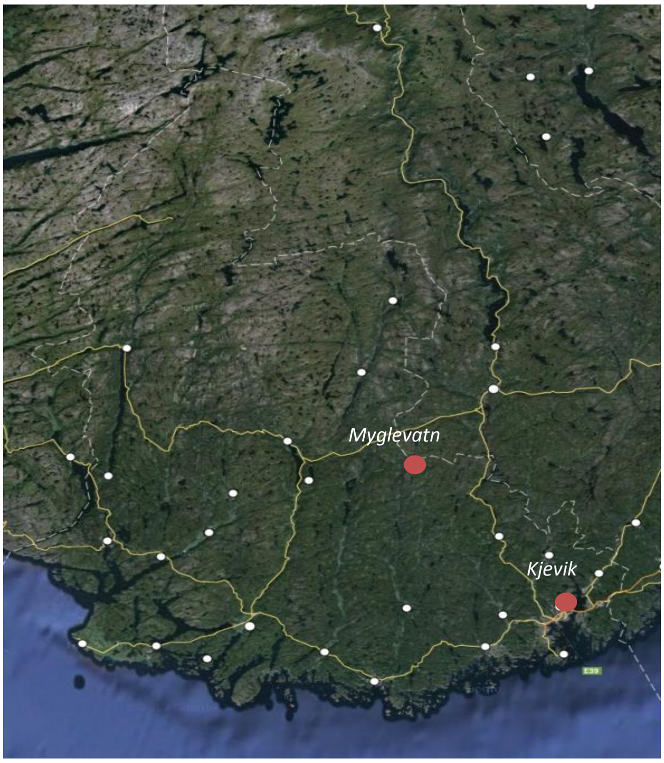
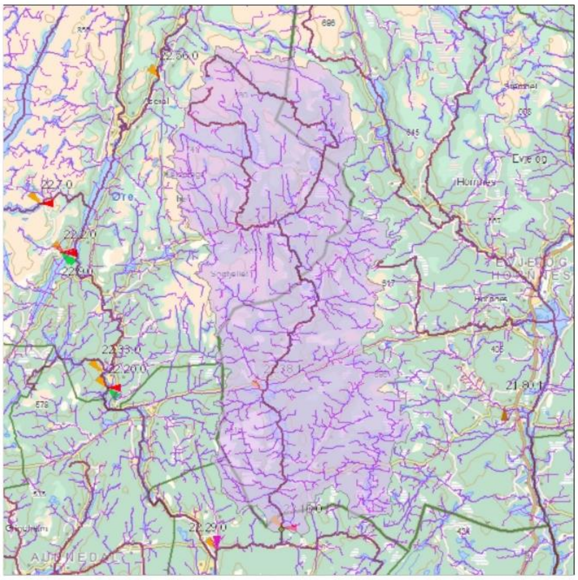


Figure 4-5 Myglevatn and Kjevik station located inside Vest-Agder County (bordered by white dashes)

The model is calibrated in the following catchment, which features are extracted from NVE (Figure 4-6).



Norges vassdrags- og energidirektorat

NVE

Kartbakgrunn: Statens Kartverk

Kartdatum: EUREF89 WGS84

Projeksjon: UTM 33N

Nedbørfeltgrenser, feltparametere og vannføringsindekser er automatisk generert og kan inneholde feil. Resultatene må kvalitetssikres.

Lavvannskart

Vassdragsnr.: 022.CA2
Kommune: Marnardal
Fylke: Vest-Agder
Vassdrag: KOSÅNA

Vannføringsindeks, se merknader	
Middelvannføring (61-90)	44,8 l/s/km²
Alminnelig lavvannføring	0,0 l/s/km²
5-persentil (hele året)	0,0 l/s/km²
5-persentil (1/5-30/9)	0,0 l/s/km²
5-persentil (1/10-30/4)	0,0 l/s/km²
Base flow	0,0 l/s/km²
BFI	0,0

Klima	
Klimaregion	Sor
Årsnedbør	1561 mm
Sommernedbør	606 mm
Vinternedbør	954 mm
Årstemperatur	4,1 °C
Sommertemperatur	10,3 °C
Vintertemperatur	-0,2 °C
Temperatur Juli	12,5 °C
Temperatur August	12,4 °C

Feltparametere	
Areal (A)	182,6 km²
Effektiv sjø (S_{eff})	1,7 %
Elvelengde (E_L)	37,4 km
Elvegradient (E_G)	11,0 m/km
Elvegradient$_{1085}$(G_{1085})	6,1 m/km
Feltlengde(F_L)	23,8 km
H_{min}	251 moh.
H_{10}	335 moh.
H_{20}	370 moh.
H_{30}	398 moh.
H_{40}	423 moh.
H_{50}	447 moh.
H_{60}	471 moh.
H_{70}	498 moh.
H_{80}	524 moh.
H_{90}	570 moh.
H_{max}	743 moh.
Bre	0,0 %
Dyrket mark	0,4 %
Myr	12,1 %
Sjø	5,5 %
Skog	63,6 %
Snaufjell	10,8 %
Urban	0,0 %

Det er generelt stor usikkerhet i beregninger av lavvannsindekser. Resultatene bør verifiseres mot egne observasjoner eller sammenlignbare målestasjoner.

I nedbørfelt med høy breprosent eller stor innsjøprosent vil tørrværsavrenning (baseflow) ha store bidrag fra disse lagringsmagasinene.

Figure 4-6 Characteristics of Myglevatn catchment

The model calibration is performed with some default values such as the evapotranspiration values. The model simulation is carried out by trying large number of free parameters combinations and by checking the good correspondence between the observed and simulation values.

The final values for the free parameters in the calibration fall inside the ranges established in the Pine HBV by Trond Rinde (Dr. Ing and Hydro informatics in NTNU). It is also noticed that the parameter logic is maintained (KLZ<KUZ1<KUZ2). They are presented in the Table 4-1.

Name	Meaning	Units	Final value
RCORR	Precipitation correction –rainfall	-	1.174
SCORR	Precipitation correction –snowfall	-	0.75
TX	Threshold temperature snowmelts	°C	3.40
TCGRAD	Temperature lapse rate for clear days	°C/100m	-0.60
TPGRAD	Temperature lapse rate during precipitation	°C/100m	-0.40
PGRAD	Precipitation lapse rate	%/100m	5
CX	Degree-day-factor	mm/ °C day	4.1
TS	Threshold temperature snowmelts	°C	-0.9
CXN	Degree-day-factor in forest	mm/ °C day	4
TSN	Threshold temperature snowmelts in forest	°C	0.56
CFR	Re-freezing efficiency in snow	-	0.02
FC	Field capacity in soil moisture zone	mm	320
LP	Threshold value for	% of FC	0.9
β	Parameter in soil moisture routine	-	3.5
KUZ2	Recession constant in upper zone	mm/day	0.446
UZ2	Threshold level for quick runoff in upper zone	mm	48.89
KUZ1	Recession constant in upper zone	mm/day	0.274
UZ1	Threshold level for quick runoff in upper zone	mm	32.52
KUZ	Recession constant in upper zone	mm/day	0.067
PERC	Percolation from upper to lower zone	mm/day	0.60
KLZ	Recession constant in lower zone	mm/day	0.04

Table 4-1 Table with the final parameters values obtained in the calibration of the Pine HBV

Finally, the model calibrated with all the free parameters set a final R^2 value for the calibration period of 0.71.

As shown in the following figure, the accumulated difference has no trend and the accumulated runoff, both observed and simulated, have a good correspondence within the calibration period.

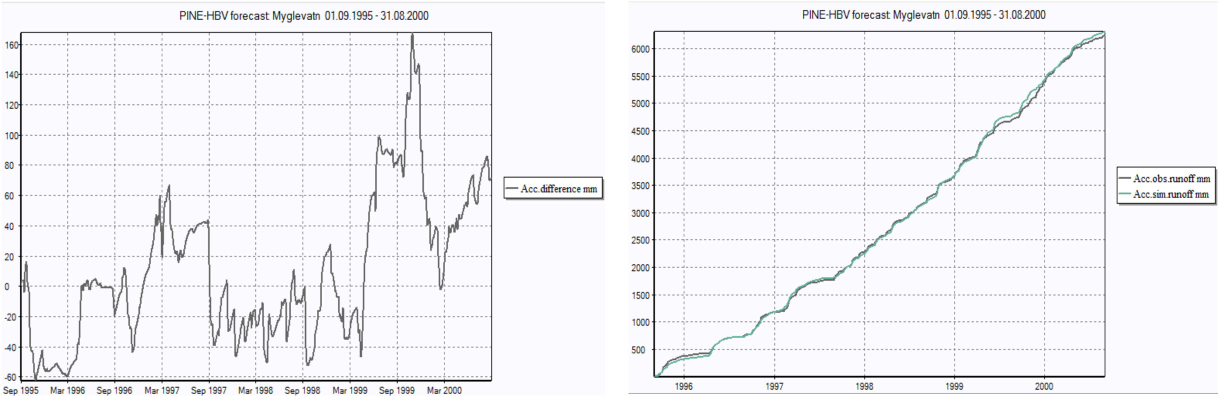


Figure 4-7 Accumulated difference (mm) and accumulated runoff observed and simulated (mm) in period 1995-2000

4.4 Model validation

Before the model validation is performed, there is a need to validate and check the quality of the inputs to the HBV model. Therefore, double mass curve which is a very effective technique is applied to check the consistency of the data recorded between two stations. So, Kjevik cumulative precipitation (1971-2000) is plotted against Sirdal cumulative precipitation (1974-2000) in the figure below:

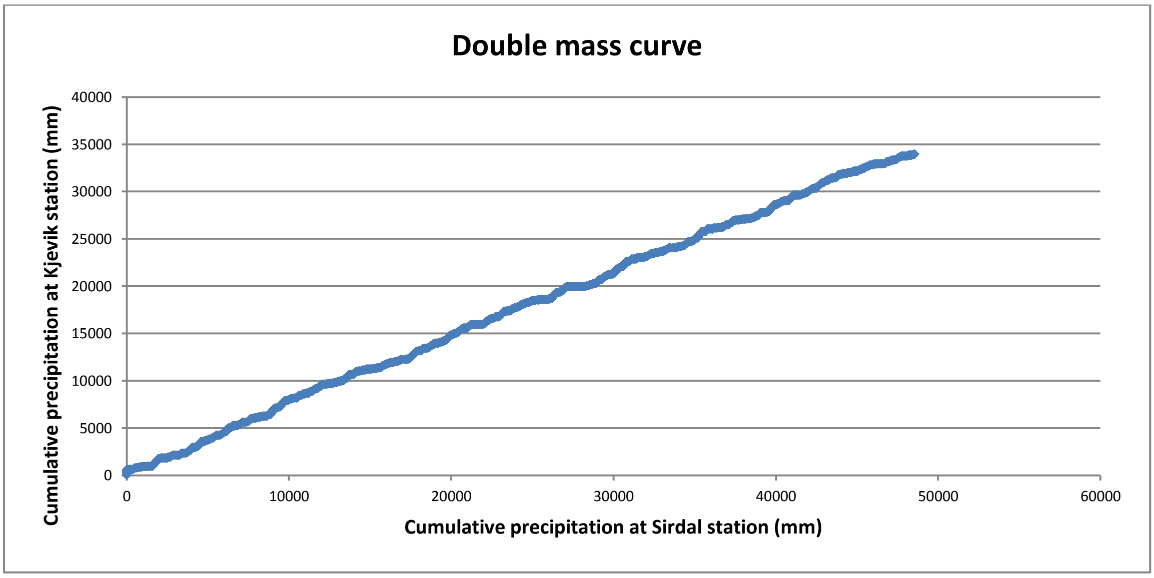


Figure 4-8 Double mass curve for Kjevik and Sirdal station.

As observed in the figure above, a straight line is computed which implies that the data from Kjevik is consistent with the data from Sirdal.

Then, validation of the model is performed by applying the parameters obtained on 5 years period (1990-1995, 1985-1990 and 1980-1985).

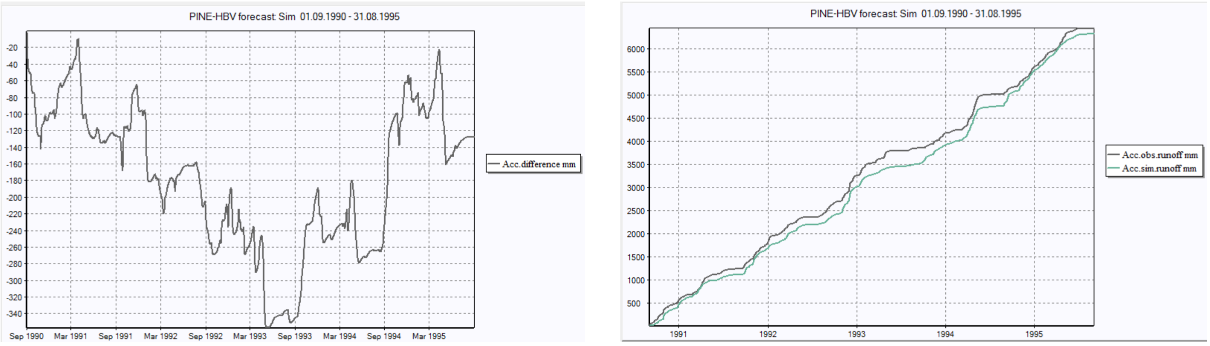


Figure 4-9 Accumulated difference (mm) and accumulated runoff observed and simulated (mm) period 1990-1995

Accumulated difference for the period 1990-1995 has no trend and the accumulated runoff, both observed and simulated, have sufficient correspondence within the validation period.

Moreover, the results of R^2 are shown below:

Period	R^2
1990-1995	0.6
1985-1990	0.609
1980-1985	0.717

Table 4-2 R^2 values obtained on the model validation

By observing the R^2 values, it is curious to note that as older the data is, a better agreement is shown judging by R^2 values.

4.5 Results and conclusions

The main purpose of applying the HBV model is to obtain the future runoff for the 2071-2100 not only to analyze and study the differences in comparison to the observed runoff but also to proceed into the next step in the current thesis. Thus, once the model is calibrated and validated, the future scenarios of delta change of Kjevik station are run with the HBV obtaining the daily average simulated runoff as illustrated in Figure 4-10.

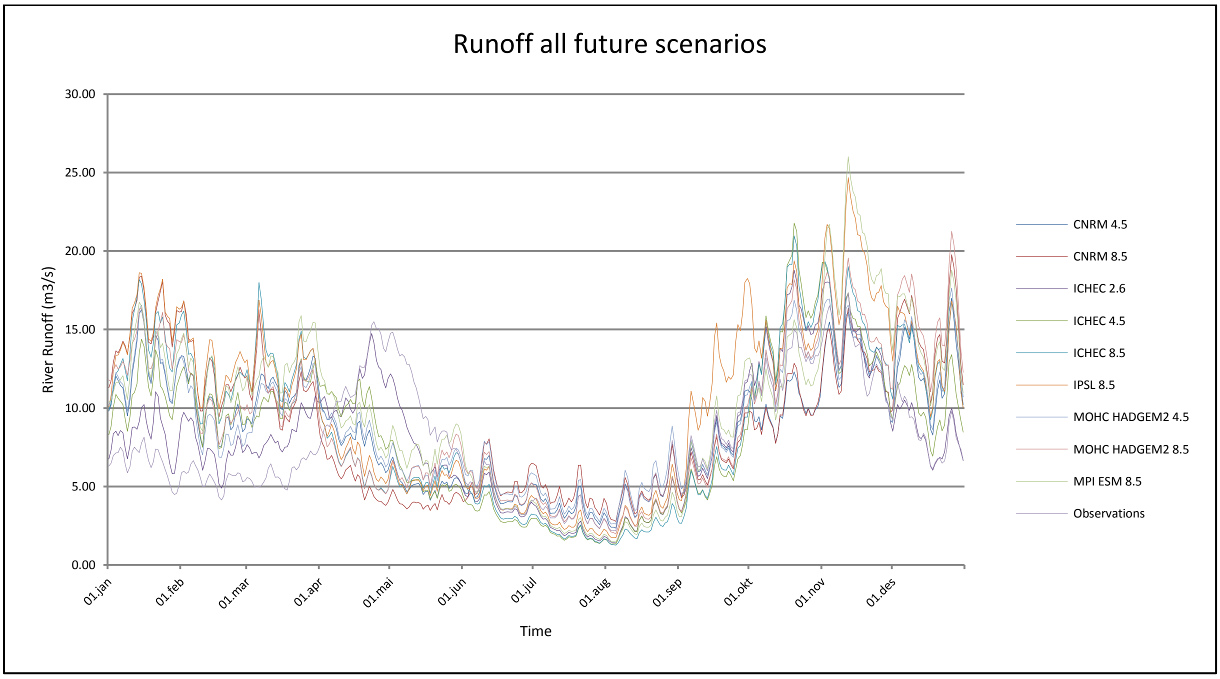


Figure 4-10 Daily average mean runoff outputs from HBV for each of the scenarios of delta change values in Kjevik for 2071-2100 period and observed values for 1971-2000 period.

It is worthwhile mentioning that results from ICHEC 2.6 are the closer ones to observed data. This is related to the fact that scenario 2.6 implies less radiative forcing and less CO^2 equivalent in the future conditions as mentioned in the section 1.2.3.

Future simulations present seasonal changes in comparison to observed values. In order to see it clearer, the lower quartile (Q1) and upper quartile (Q3) of daily average mean runoff for all scenarios is presented in Figure 4-11.

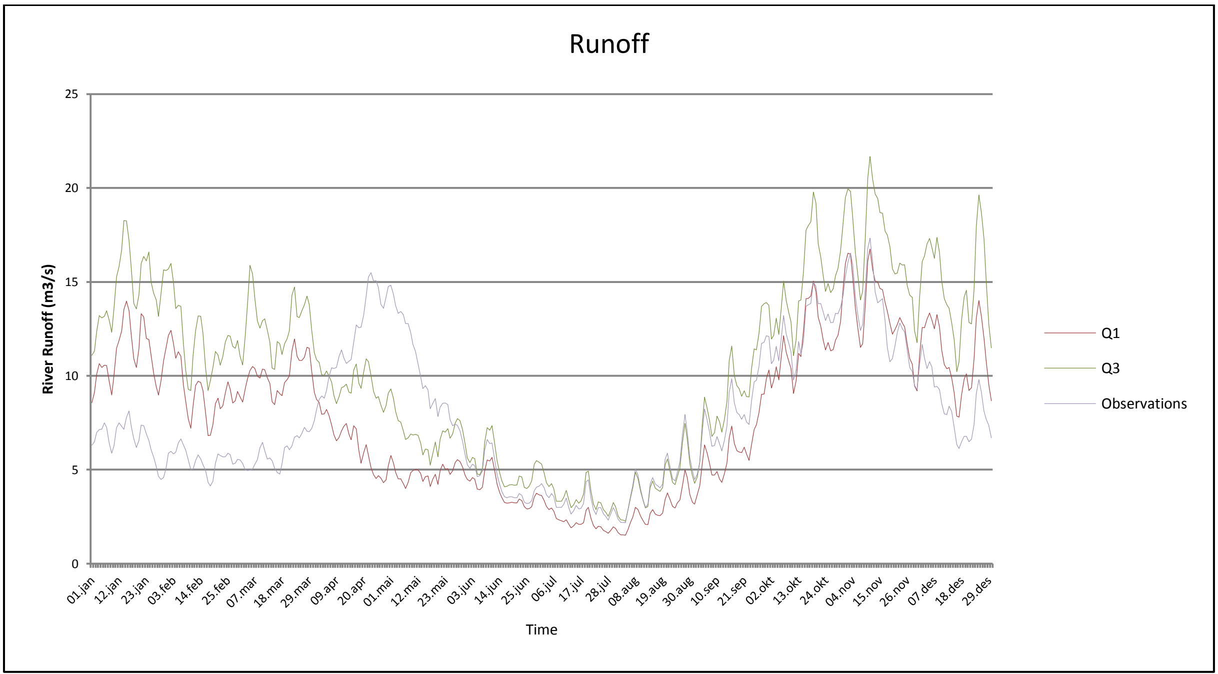


Figure 4-11 Lower quartile (Q1) and upper quartile (Q3) of daily average mean runoff of all scenarios of delta change values in Kjevik for 2071-2100 period compared to the observed runoff 1971-2000

On one hand, the future simulations predicts higher runoffs from December to March, both included, and lower ones in April and May. On the other hand, from June to November, no noticeable changes are appreciated.

A more visual graph is presented which illustrates the observed data against the mean of all simulations where the total (100%) is considered as the sum of both (Figure 4-12).

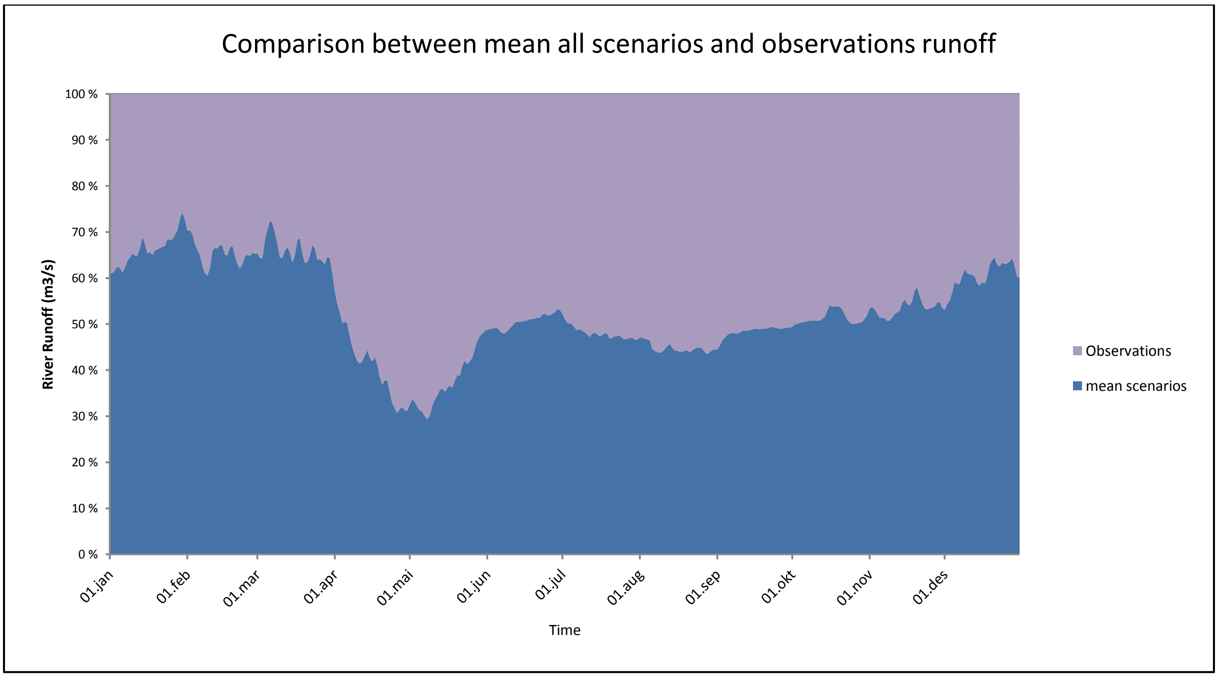


Figure 4-12 Comparison between mean all scenarios and observations runoff considering their sum as the total sum (100%)

An increase of 15% of the average daily runoff is predicted in 2071-2100 apart from the seasonal changes.

The disappearance of the spring peak of runoff could be related to the less snowpack in winter due the rise of temperatures. Besides, less accumulate snow in winter will affect the amount of snowmelt runoff in spring. Earlier snow-melts will also occur which will result in more runoff in winter and less in April and May. Thus, snowmelt and snowpack are also analyzed below.

The snow melt is the runoff from the melting snow (mm) and it can be also extracted with the Pine HBV.

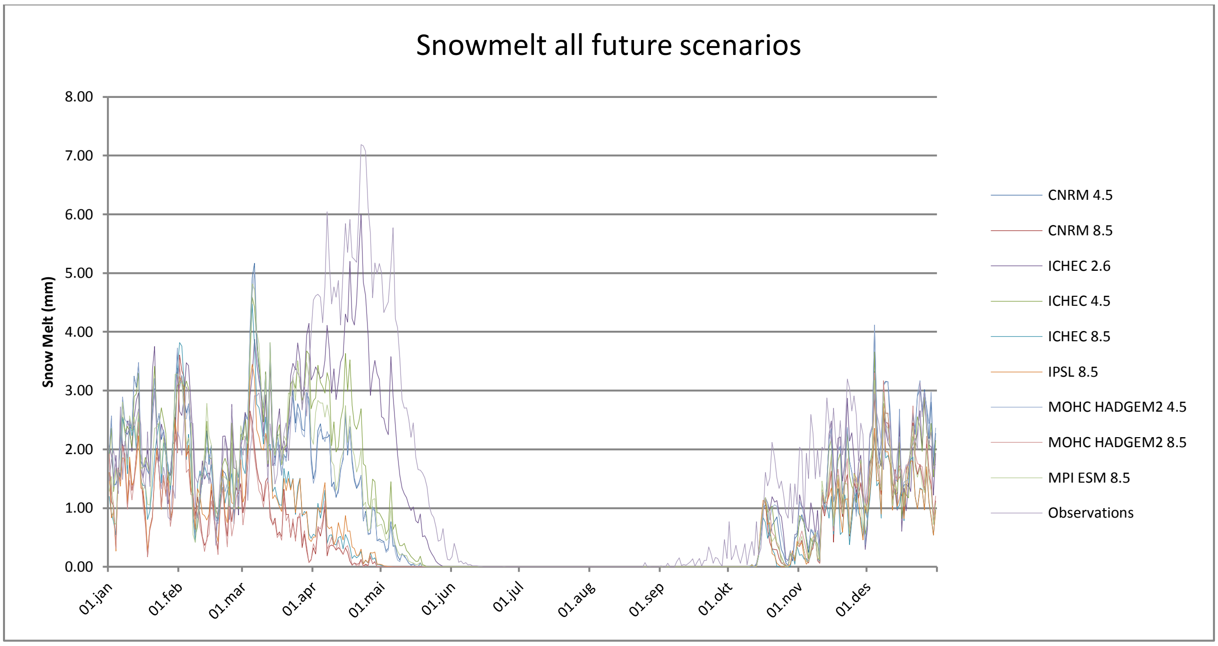


Figure 4-13 Daily average mean snowmelt outputs from HBV for each of the scenarios of delta change values in Kjevik for 2071-2100 period and observed values for 1971-2000 period.

Different tendencies are observed according to the new scenarios and again the results from ICHEC 2.6 are the closer ones to observation data.

Future simulations present seasonal changes in comparison to observed values. The lower quartile (Q1) and upper quartile (Q3) of daily average mean snowmelt for all scenarios is presented in Figure 4-14.

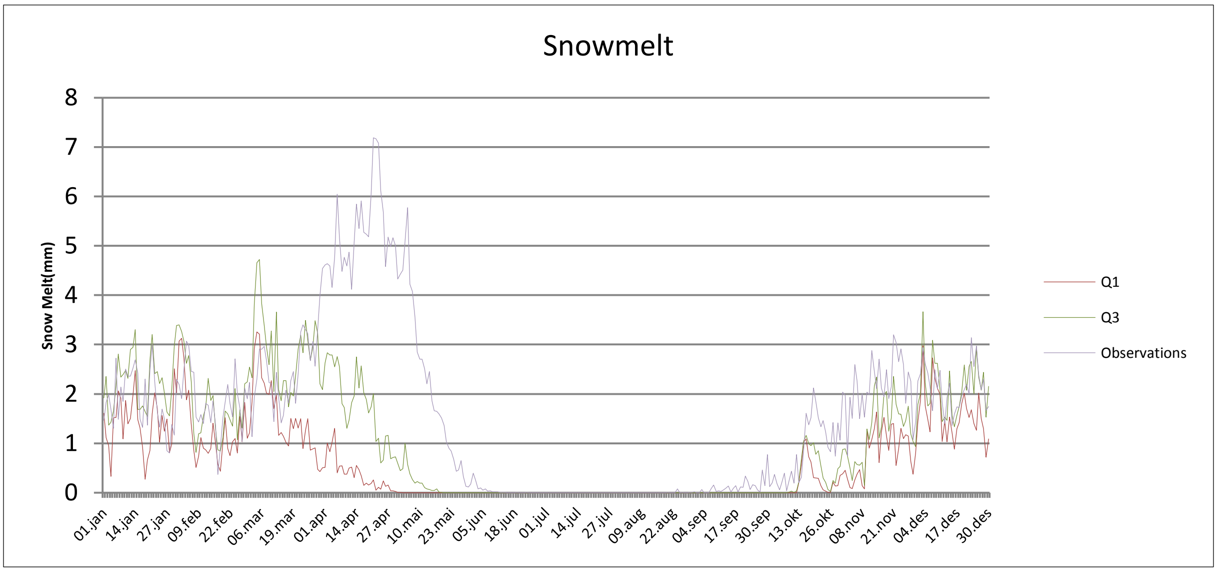


Figure 4-14 Lower quartile (Q1) and upper quartile (Q3) of daily average mean snowmelt of all scenarios of delta change values in Kjevik for 2071-2100 period compared to the observed runoff 1971-2000

In the Figure 4-14 a considerable reduction of snowmelt is illustrated mainly in spring as expected above. Therefore, the decrease in spring runoff simulations is related to the less spring snowmelt simulations. In general, an average reduction of 46% is concluded in snowmelt between both periods.

The follow graphs make an analysis of the predicted snowpack in the catchment. The snowpack, which measures the average thickness layer of snow accumulated (mm), is also an outcome of Pine HBV model.

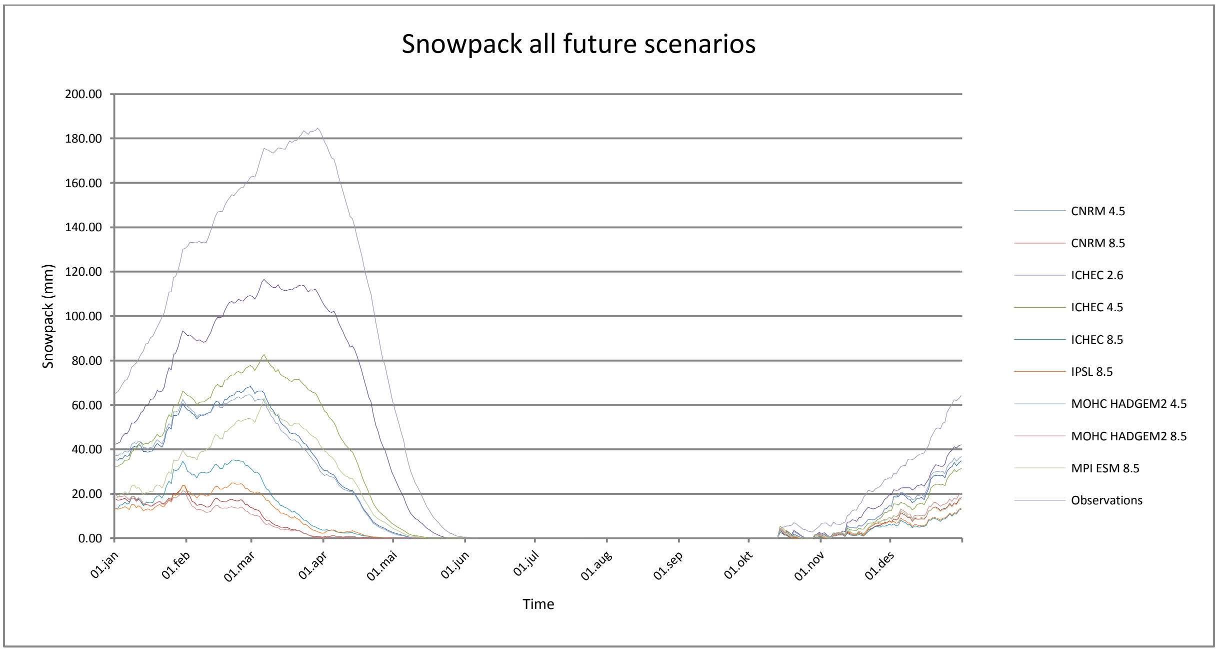


Figure 4-15 Daily average snowpack outputs from HBV for delta change values in Kjevik for 2071-2100 period and observed values for 1971-2000 period.

A substantial difference in the snow pack is observed between observations and future values according to the HBV simulations. It is clearly noticed that all new scenarios indicate a considerable decrease in the snow pack. In general, 3 different subsets of scenarios can be identified in the graph above: firstly, models developing the RCP8.5 scenario present the higher loss of snowpack; secondly, models of the RCP4.5 scenario suggest less loss of snowpack but still large compared to the observed data; and the ICHEC 2.6 scenario that presents the less snowpack loss.

The same conclusions can be extracted by observing the graph with lower quartile (Q1) and upper quartile (Q3) values of daily average mean snowpack.

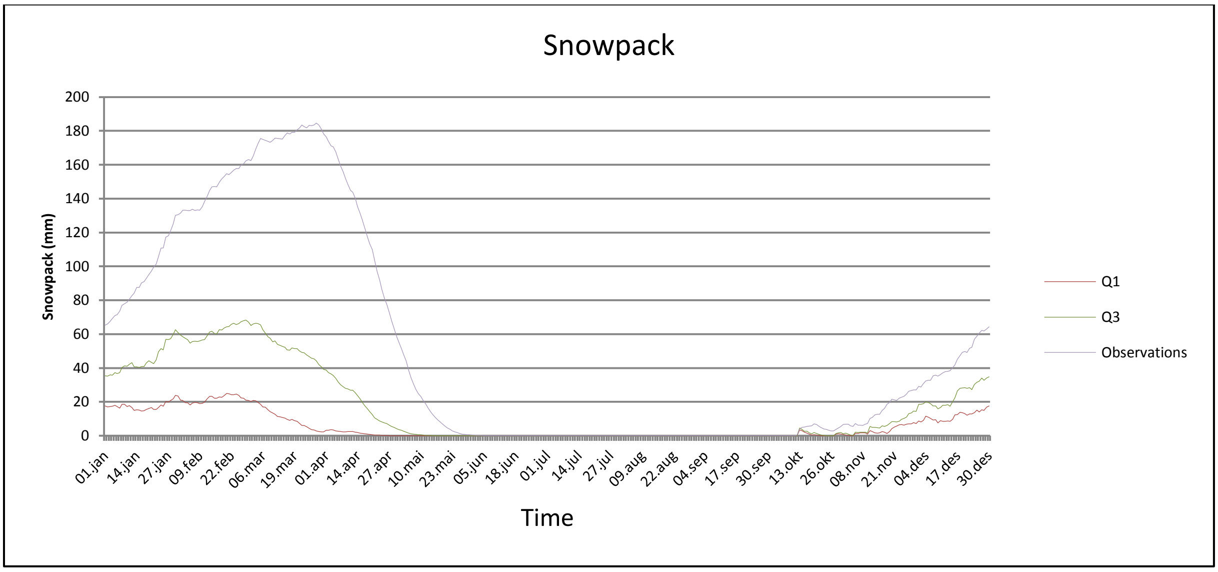


Figure 4-16 Lower quartile (Q1) and upper quartile (Q3) of daily average mean snowpack of all scenarios of delta change values in Kjevik for 2071-2100 period compared to the observed snowpack 1971-2000.

Finally, the mean of all models and scenarios in 2071-2100 indicates a significant reduction of 74% on the snowpack in comparison to the values observed in 1971-2000. In fact, a report by the Norwegian Meteorological Institute also reached a similar conclusions (Schuler, Beldring et al. 2006).

5 nMag model

5.1 Introduction

The program nMag is a model for simulating the reservoir operation and the power production in a hydropower system. It is able to describe the hydrological and hydraulic conditions in the production system in an accurate way and the operational strategy and the consumption system slightly more simply.

The ENMAG hydropower simulation model has been developed at the Norwegian Hydrotechnical Laboratory, which is affiliated to SINTEF and the Norwegian Institute of Technology in Trondheim in 1984-86. In this study nMag 2004 is used to perform the simulations.

The case of the present project is focus on the Mandalselva River which is located southern Norway (58ºN, 7ºE). The catchment covers approximately 1800 km^2 and it is classified as one of the largest in southern Norway. The Mandalselva River has a length of 115 km and a mean annual discharge of 88 m^3 s^{-1}. It is regulated by 6 hydropower plants and the system has 9 natural and artificial lakes used as reservoir by the power plants. The system has 2 main lakes, Navann and Juvatnet, which represent the 90% of the storage capacity.

The model used to simulate the *Mandalselva* hydropower system it is already given and it is composed of the following modules shown in figure 5-1. The use of this model allows the user to knowhow the discharge is distributed in the power plant systems when no measured data are available.

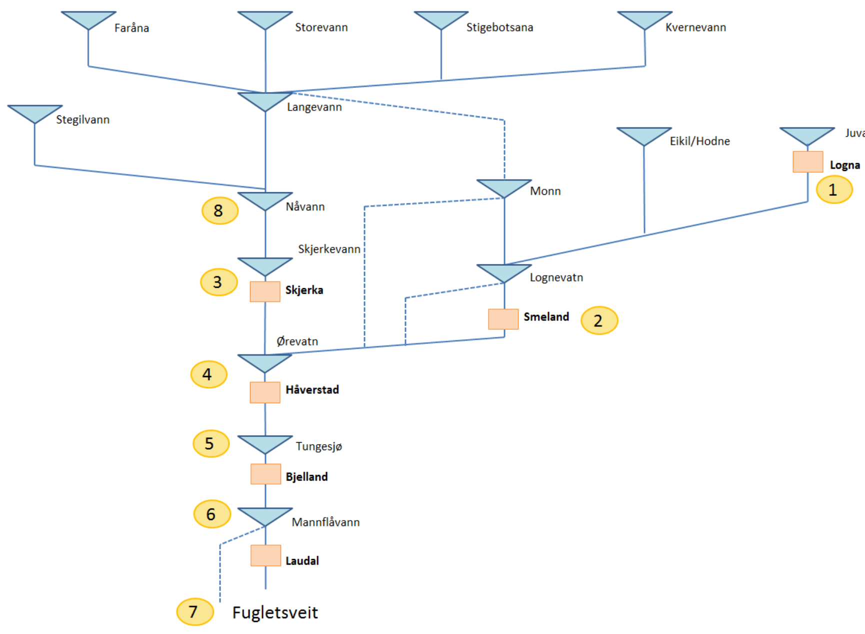


Figure 5-1 Representation of Mandal river power system in the nMag model. The triangles represent the several subcatchments, the oranges rectangles indicate the powers plants and the numbers inside the yellow circles design the module number. Dotted lines indicate environmental flow restrictions.

The software of nMag 2004 can provide many information of each of the modules. The current study is focused on the module number 6 (Laudal) because it is considered the most relevant point since it is the basin outlet of the catchment of Mandal, so the lowest in the Mandal water system.

Figure 5-2 Laudal power plant. Extracted from Agder Energy web page.

According to the Agder energy, Laudal power plant (1981) is built into the mountain and has its intake in the reservoir in Mannflåvann. It has 2 Francis turbines with a vertical height of 36 meters. Some other features are listed below (Table 5-1)

Facts	
Intake	Mannflåvann
Head	36 m
Tunnel Length	5900 m
No. of Generators	2
In Operation	1981
Maximum Output	26 Mw
Average Annual Production	146 Gwh

Table 5-1 Facts about Laudal power plant.extract from the Agder energy.

5.2 Methods

The inputs used in nMag are taken from the outputs of HBV model. They are the daily river flows (m^3/s) for the period 2071-2100 considering the several models and scenarios of Delta change.

It is important to notice that in order to continue, it is assumed that the same scale factor of Myglevatn, where the HBV have been calibrated, can be applied to the whole catchment of the Mandal River. This assumption could add some uncertainties to the final results but this decision is made in order to proceed with the study.

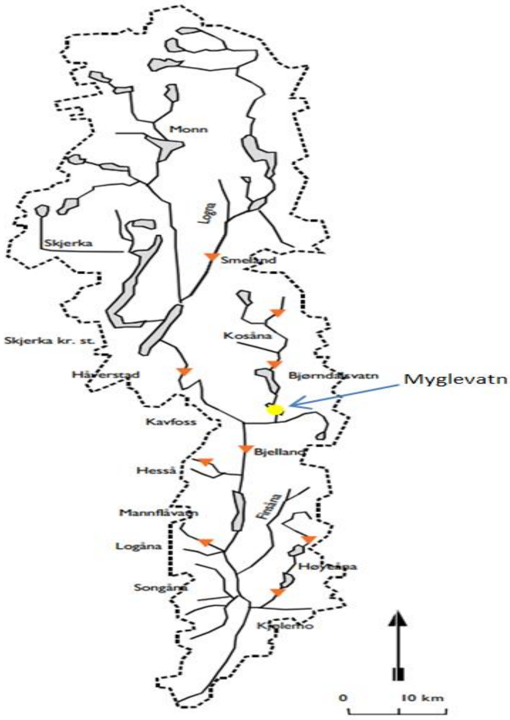


Figure 5-3 Map of the closest subcatchments and power plants near to Myglevatn Lake. Extracted from the document "Liming of salmon rivers in Norway; success depends on sophisticated strategy and organization" from Directorate for Nature management

Figure 5-4 Mandalselva catchment located in Norway. Extracted from the document "Proceedings of the Acid Rain Mitigation Workshop" from Environment Canada Atlantic Region.

This factor (f_j) is calculated as the ratio between the average runoff of Myglevatn in the period 1971-2000 and the average runoff of Myglevatn for the several scenarios in the period 2071-2100.

$$f_j = \frac{\bar{Q}_{myglevatn\,scenario}}{\bar{Q}_{myglevatn\,1971-2000}}$$

Where,

$f_j: Correct\ factor\ for\ the\ scenario\ j$

$\bar{Q}_{myglevatn\,scenario}: Average\ runoff\ for\ all\ the\ period\ 2071 - 2100\ for\ scenario\ j\ (\frac{m^3}{s})$

$\bar{Q}_{myglevatn\,1971-2000}: Average\ runoff\ for\ all\ the\ period\ 1971 - 2000\ (\frac{m^3}{s})$

A table of the $\bar{Q}_{myglevatn\,1971-2000}$ values and f_j numbers are presented in Table 5-2.

Number Module	Average annual runoff (mill m^3)
Module 1: Juvatn/Logna	358
Module 2: Lognevatn/Smeland	235.3
Module 3: Skjerkevatn/Skjerka	9.5
Module 4: Ørevann/Håverstad	225
Module 5: Tungesjø/Bjelland	195
Module 6: Mannflåvatn/Laudal	463
Module 7: Fuglestveit	0
Module 8: Nåvann	812.2

Table 5-2 $\bar{Q}_{myglevatn\ 1971-2000}$ values of the different models

Model and Scenario	f_j
CNRM RCP 4.5	1.09
CNRM RCP 8.5	1.13
ICHEC RCP 2.6	1.03
ICHEC RCP 4.5	1.08
ICHEC RCP 8.5	1.15
IPSL RCP 8.5	1.30
MOHC HADGEM2 RCP 4.5	1.16
MOHC HADGEM2 RCP 8.5	1.18
MPI ESM RCP 8.5	1.26

Table 5-3 f_j correcting factor due to the model and scenario

It is observed that all the f_j correcting factor values are above 1, which means that in the future 2071-2100 period, the runoff is thought to increase according to all the models and scenarios.

As we moved ahead, the next step is to apply f_j to the average annual runoff (mill m^3) for all the modules of the catchment on the corresponding scenario:

$$T_{ij} = S_i . f_j$$

Where,

$T_{ij}: Average\ annual\ runoff\ for\ module\ i\ corrected\ for\ scenario\ j\ (mill\ m^3)$

$S_i: Average\ annual\ runoff\ for\ module\ i\ (mill\ m^3)$

$f_j: Correct\ factor\ for\ the\ scenario\ j$

The T_{ij} values are used as the inputs on the nMag in order to scale all the data due to the scenario that it is being analyzed.

5.3 Results and conclusions

The follow section analyzes the prediction results extracted with nMag from Laudal (module 6): the total inflow and the power production of the Laudal power plant.

First, the total inflow of Laudal power plant is illustrated categorized by all the models and scenarios.

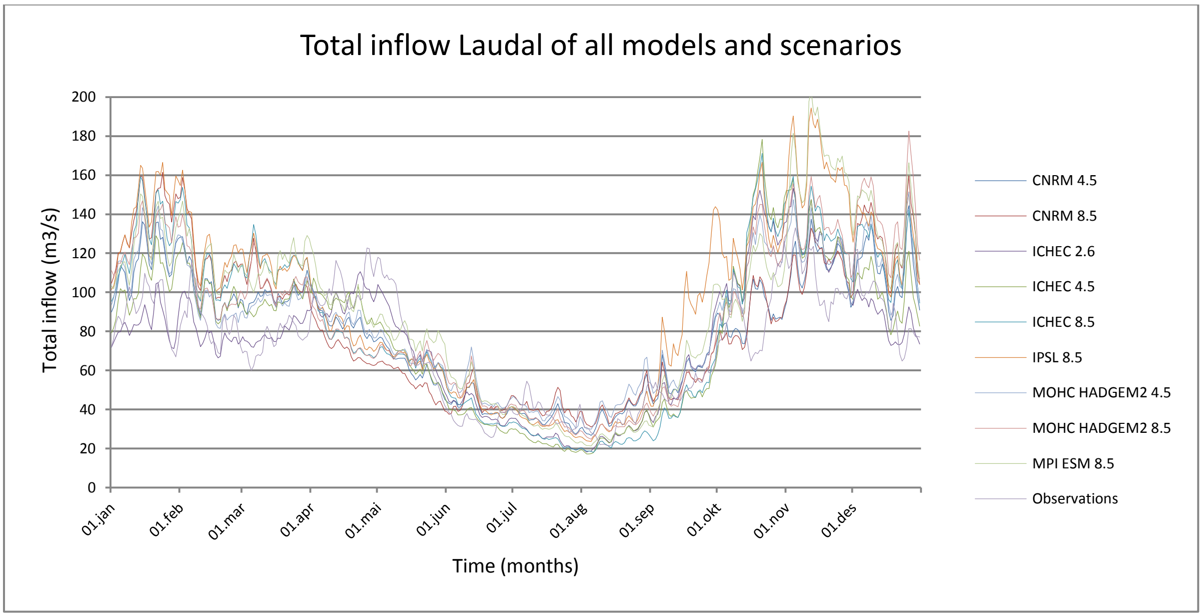


Figure 5-5 Average daily total inflow of Laudal (m3/s) of observed data for the period 1971-2000 and values obtained according to the model and scenario for the period 2071-2100

Despite the fact that Figure 5-5 shows slight differences between models and scenarios, most of them follow the same trend: a rise of runoff in winter and autumn and a decrease in the beginning of the spring.

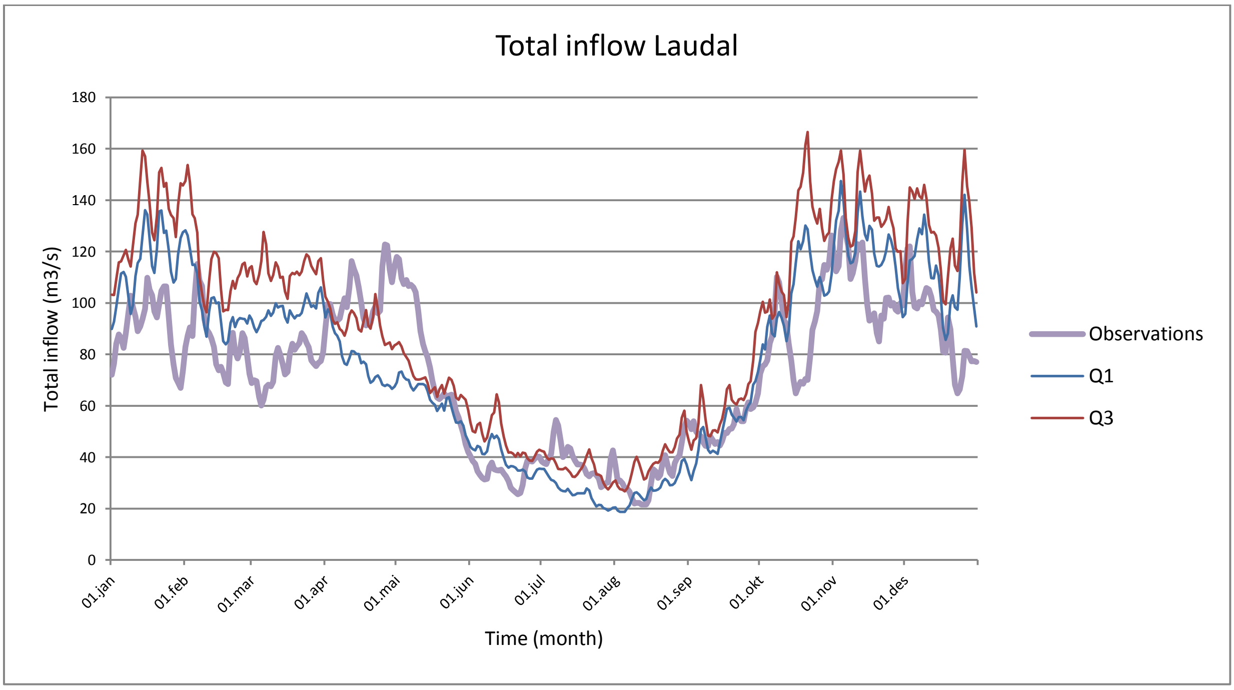


Figure 5-6 Average daily total inflow of Laudal (m^3/s) of observed data for the period 1971-2000 and values obtained according to the Q1 and Q3 of all models and scenarios for the period 2071-2100.

When the lower quartile or Q1 and the upper quartile or Q3 of predicted values in the future are compared to observed data, the same trends as in Figure 5-5 are observed: observations values stay mostly below the Q1 in autumn and winter and above Q3 in late spring.

The mean of the models (2071-2100) indicates an increase of 15% in the annual total inflow in Laudal compared to the observed data in 1971-2000. Thus, in addition to present seasonal changes also increase the annual total inflow.

Certainly, runoff and power production are two variables that are often related. Thus, power production of Laudal power plant categorized by models and scenarios is plotted below:

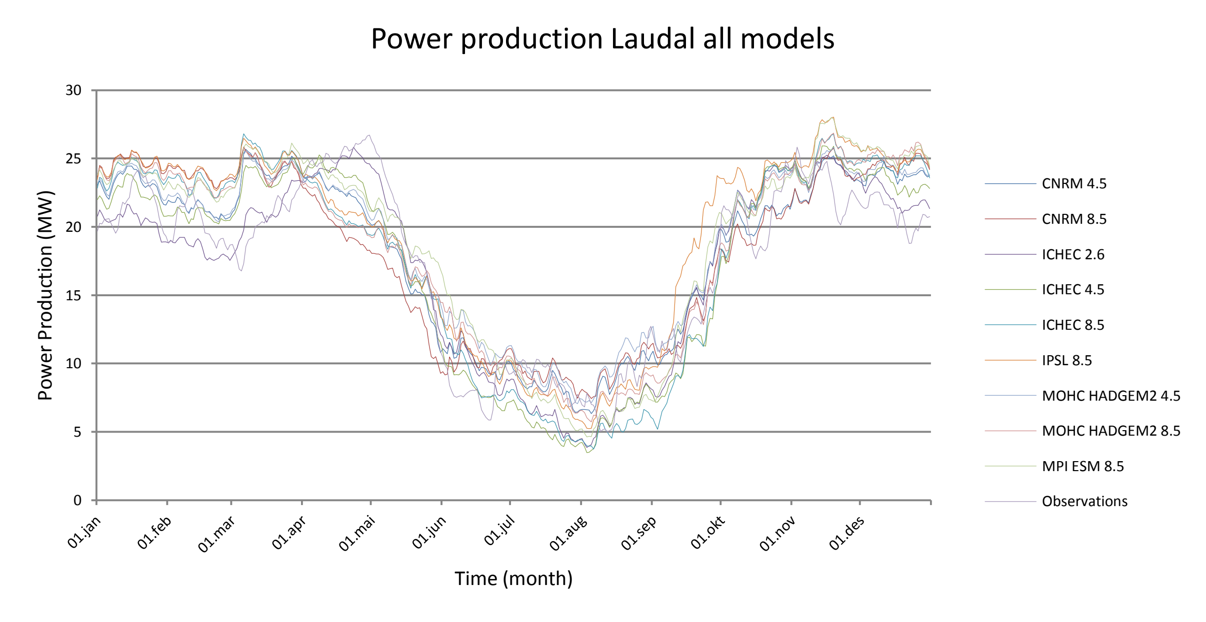


Figure 5-7 Average daily power production of Laudal (MW) of observed data for the period 1971-2000 and values obtained according to the model and scenario for the period 2071-2100

On one hand, future power production of Laudal power plant with its current structure presents a growth in the late autumn, winter and begining of spring. Additionally, an increment of power production is predicted in June. On the other hand, a significant reduction is appreciated in April and May, which coincide with the decrease of runoff. The same tendency is observed on the following graph where the quartiles (Q1 and Q3) are presented:

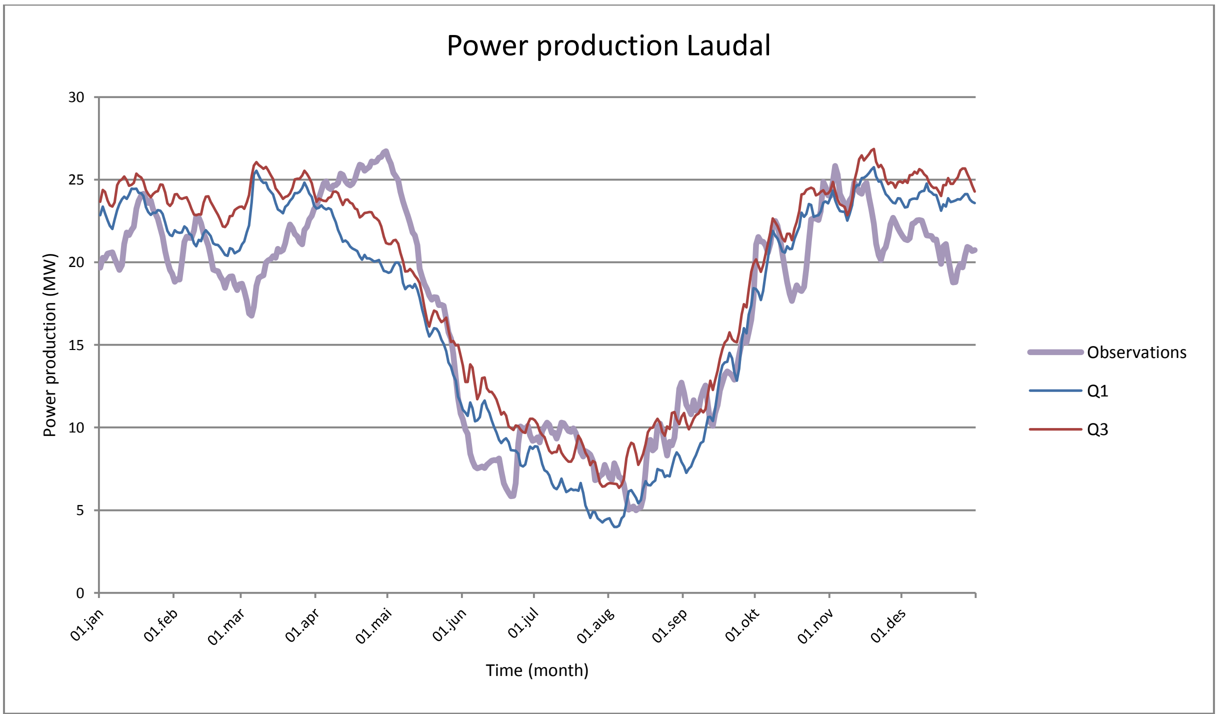


Figure 5-8 Average daily power production of Laudal (MW) of observed data for the period 1971-2000 and values obtained according to the Q1 and Q3 of all models and scenarios for the period 2071-2100.

Despite the seasonal fluctuations in power production, Laudal power plant shows an increment of 4% on the average annual power production in the future compared to the observed data. The observed data results in an annual production of 153 Gwh and future values predict 159.4 Gwh. Thus, the annual production will increase in 6.4 Gwh.

In conclusion, according to the future predictions more homogeneous runoff will be observed because of the earlier snow-melts and less snow accumulated. Thus, the runoff peak detected in spring on the observations will disappear. These changes in the runoff distribution will alter the power production distribution in Laudal power plant and increase its annual production, fact that have to be taken into account in further studies to future changes of the hydropower systems.

6 Conclusions

The main conclusions are presented in a sequential order below despite that fact that each chapter is already equipped with necessary discussions and conclusions.

The main aim of this study is to study the impact of the climate change on the Vest-Agder, specifically in Mandal catchment. To reach conclusions, different downscaling tools and bias correction methods have been performed and a comparison between the outcomes is assessed. In general, all the models performed satisfactory and the data is reliable. All of them have a very good agreement in temperature and in precipitation only Engen-Skaugen bias correction method presented differences, which leads to the conclusions that there is a need to be very careful when applying this method to the precipitation data. In addition, an increment between 2 and 4 ºC is found in 2071-2100 compared to 1971-2000. An increase of precipitation is predicted and though seasonal differences between stations are observed, all 3 point in more precipitation in winter and beginning of spring. These disagreements in precipitation by applying the bias correction method lead to the choice of Delta change predictions values based on RCM to proceed in the study.

The HBV model has been calibrated on Myglevatn with its data of river flow and with observed data of precipitation and temperature from Kjevik station on the calibration period 1995-2000. The value observed of Nash efficiency (R^2) is 0.71. Accumulated runoff throughout the time period and also the accumulated difference has been checked.

Model validation is carried out in other 5 years period within the data available (1985-1990, 1990-1995, 1995-2000) obtaining values of R^2 between 0.6 and 0.71 with no clear tendencies in the accumulated runoff and differences.

Then, HBV is run with Kjevik station data with delta change applied for all scenarios and models to predict runoff and snow pack in the future period (2071-2100) and compare them to the calibration period (1971-2000). An annual increment of 15% is found in runoff with increases from December to March and reductions in April and May. The results show a decrease of 74% in snowpack and reduction in snowmelt of 46% with differences among the scenarios.

Next, nMag software is used to make an assessment with the runoff outputs from HBV on the hydropower system within the Mandal catchment. An assumption is made in that point applying the same scale factor of Myglevatn to the rest of the catchment selected. The power plant situated in Laudal, the most relevant point of the catchment, was analyzed. Total inflow increases in winter and autumn and decreases in April and May. Although these seasonal fluctuations, an increment of 15% is showed in the annual total inflow.

Additionally, power production indicates an increase of 6.4 Gwh, which represents a growth of 4% in comparison to the period 1971-2000.

Therefore, it is very important to analyze the future impacts due to the climate change to anticipate and optimize the hydropower systems, particularly in Norway where they have a large presence. In fact, dams, tunnels, reservoirs and power plants that are built now will remain for a long time and will be affected by the future conditions.

7 Limitations and future work

In conclusion, although all the predictions applied with different downscaling method points at the same direction, there is a need to develop more accurate bias correction methods to approach better the conditions in the future and in the local scales, especially in precipitation where more spread results were found. In this kind of procedures, the uncertainty needs always to be taken into account and it is necessary to proceed.

The results from the HBV model calibration can be improved if real values of evaporation values were used instead of default values given by the Pine HBV software.

For the current study, only one RCM point was selected to represent a station, the one that was closer. However, more reliable results would have been achieved if more than one RCM point were selected for each station.

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9 Appendices

9.1 Appendix A: ARCGIS procedure

Making point and area shapefiles to identify stations and select area with RCM points

Make a Point shapefile from selected Stations

1. Create an excel workbook file with all the selected stations that you will potentially work with the headings “Name”, “Latitude” and “Longitude”, see example below (Stations_v3-xls//VestAgderStations.xls):

Station name/ID	Longitude	Latitude
Finsland	7.59	58.32
Bjelland	7.53	58.35

Note I: Select the stations according to data available (i.e. stations with good historical data), but also good to plot as many as possible to get a feeling of what is close to what.

Note II: Station selection, data on their latitude/longitude and timeseries data on precipitation and temperature can be found and downloaded for free at Norwegian Meteorological Institute (eklima.met.no).

Note III: To select stations according to the availability of old scenarios prediction data on (http://noserc.met.no/effect/dynamic/index.html). Go to refined results and select the county in which your area is.

2. Create a Point shapefile from the excel file
   - Open ArcMap 10 and go to ArcCatalog (If not active, Windows/ArcCatalog)
   - Click on Folder connections and find the folder in which your excel file was created (if it is not there, right click and *Connect Folder* and then look for the folder). In our case:
     C:\CLIMADOWN\SupportingDocs\Stations\Coord
   - Find your excel file and click on the ‘+’ symbol on the left. Select the sheet in which your data is and right click on it.
   - Select Create Feature class/From XY table
   - In the dialog table:
     - X Field = Longitude*; Y Field = Latitude*; Z Field= none
     - Click *on Coordinate System*. and Select:

Geographic Coordinate Systems/World/WGS 1984.prj
- Output location: C:\CLIMADOWN\SupportingDocs\Stations\Coord
- Then, press ok

*Note: In order to work in ARGIS, X=Long, Y=Lat

3. Visualize Point shapefile and IDs:
   - Once created (XYStations_v3), move the Point shapefile to the table of Contents in the Main ArcMap Screen (by dragging it or File/Add data) and you will be able to visualize it.
   - From this, you will be able to create an area Shapefile that encompass all the station points (see next section) or you will be able to see which points fall in an already exiting shapefile*

*Beware of the projection in the already existing shapefile, this should be converted into WGS 1984 first in order to compare with latitude/longitude data (see at the end of "Appendix A: ARCGIS procedure" how to transform projections).

Make an Area Shapefile to be used in "1.Extraction_of_points_Index_in_the_basin_step_1" (to select RCM data by clipping area)

1. Create empty Area shapefile
   - Go to ArcCatalog
   - Find folder: C:\CLIMADOWN\Step1\Input
   - Right click on the folder and select: *New / Shapefile*
   - In the dialog:
     - Name: Mandal_latlong_ext
     - Feature type: Polygon
     - Spatial Reference/Edit/Select:

       Geographic Coordinate Systems/World/WGS 1984.prj

       or

       Spatial Reference/Edit/Import:

       C:\CLIMADOWN\SupportingDocs\Stations\Coord\XYStations_v3
     - Then, press ok
2. Delimit the area, shape and size of the shapefile

- Once created (Mandal_latlong_ext), move the Area shapefile to the table of Contents in the Main ArcMap Screen (by dragging it or File/Add data). You will not be able to see anything in the main screen as it is empty.
- Go to Editor (If not able to see it go to Customise/Toolbars/Editor) and select Start Editing
- In the Start Editing Dialog you will have to choose which layer you want to edit, in this case Mandal_latlong_ext, so you should click on it and press OK
- A *Create Features* dialog will appear, click on the selected file (Mandal_latlong_est) and select the type of shape you want to construct your area with (See construction tools in the bottom of the dialog and choice between polygon, rectangle, circle… Recommended: Polygon so you are more flexible to select the desired area)
- Go to the main screen with the mouse and the pointer will now be in a '+' shape, left click and start drawing the area you want to select around the station points. Once you are finished drawing the area, press double click and the area will be drawn in the main screen.
- The go to *Editor/Save Edits* and the *Editor/Stop Editing*. Then your shapefile will be saved and ready to be used in Script 1

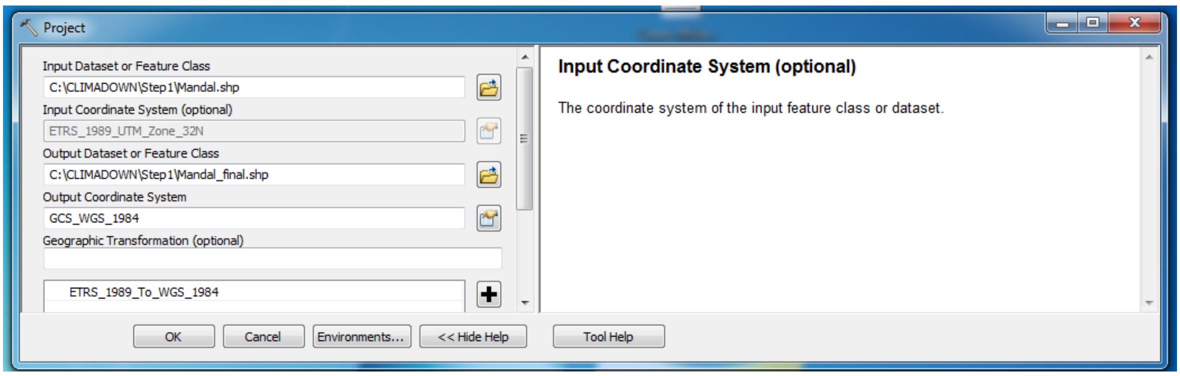
How to transform projections

In the case you already have a shapefile that you want to use to select your RCM data, it is likely that your data is not in the latitude/longitude projection system. Therefore, a transformation will be needed in order to input the shapefile into the script.

To convert to latitude and longitude:

ToolBox/DataManag.Tools/Proj& Transf/Features/Project

WGS1984 the projection needed



Make a shape file from an .xls file in order to know which point of RCM corresponds to each station

- It needs to be open in excel and saved as an excel workbook.
- Then go to ArcCatalog in ArcGIS and convert it to a point shapefile (see "**Make a Point shapefile from selected Stations"*)***
- Open both shapefiles (Stations & rr_final) and find the closes RCM point to the selected station
- Write down the code of the selected RCM points, so later it will be easy to find them.

9.2 Appendix B: Delta applied script of precipitation and temperature

The script 3.1.2 is presented for the station Kjevik (code: 120205) for precipitation and temperature.

Precipitation

```
##### SCRIPT 3.1.2

#### Done with ALL MODELS
#### RR (precipitation)
#### For 1 point --- 120205_Kjevik
#### OUTPUT: final

rm(list=ls())
library(zoo)

### Read Daily data from 1 station
st1<-read.table ("C:\\CLIMADOWN\\StationData\\120205_Kjevik_Daily_RR.csv", sep=";", header=T)

### Create final data.frame
final<-data.frame(as.numeric(rep(0,10958)))

### POINT 120205_Kjevik

#-----------------------------------------------CNRM RCP 4.5----------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_CNRM_rcp45_1971-2000_vs_2071-2100.Rdata")

    #Extract delta from the point
    delta<- t(delta_crrm_7100_to_hist_rcp_45)
    deltaf<-data.frame(delta)
    colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
    delta_120205<-deltaf[,"120205"]
    delta_120205_CNRM45<-data.frame(delta_120205)

    #Change format of Station data
    st1<-st1[-10959,]
    st1$date<-as.Date(c(365:11322), origin="1970-01-01")
    st1$month<-substr(st1$date,6,7)
    st1<-st1[,-1]
    st1$RR<-as.numeric(as.character(st1[,1]))

    #Apply delta and add column (120205_CNRM45_7100) to final
    z<-nrow(st1)
    i<-1
    final$"120205_CNRM45_7100"<-st1$"RR"
    final<-data.frame(st1[,1:2])
    mv<-format(as.Date(final$date,format="%Y-%m-%d"), "%m")
    mv<-as.numeric(mv)

    #Apply delta
    for (i in 1:z) {
      final$"120205_CNRM45_7100"[i]=st1$"RR"[i]*(1+(delta_120205_CNRM45[as.numeric(mv[i]),])/100)
    }


#-----------------------------------------------CNRM RCP 8.5----------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_CNRM_rcp85_1971-2000_vs_2071-2100.Rdata")


    #Extract delta from the point
    delta<- t(delta_crrm_7100_to_hist_rcp_85)
    deltaf<-data.frame(delta)
    colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
    delta_120205<-deltaf[,"120205"]
    delta_120205_CNRM85<-data.frame(delta_120205)

    #Apply delta and add column (120205_CNRM85_7100) to final
    z<-nrow(st1)
    i<-1
    final$"120205_CNRM85_7100"<-st1$"RR"
```

```
    #Apply delta
    for (i in 1:z) {
      final$"120205_CNRM85_7100"[i]=st1$"RR"[i]*(1+(delta_120205_CNRM85[as.numeric(mv[i]),])/100)
    }


#----------------------------------------------ICHEC RCP 2.6--------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_ICHEC_rcp26_1971-2000_vs_2071-2100.Rdata")


#Extract delta from the point
delta<- t(delta_ICHEC_7100_to_hist_rcp_26)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_ICHEC26<-data.frame(delta_120205)

#Apply delta and add column (120205_ICHEC26_7100) to final
z<-nrow(st1)
i<-1
final$"120205_ICHEC26_7100"<-st1$"RR"

#Apply delta
for (i in 1:z) {
  final$"120205_ICHEC26_7100"[i]=st1$"RR"[i]*(1+(delta_120205_ICHEC26[as.numeric(mv[i]),])/100)
}

#------------------------------------------------ICHEC RCP 4.5--------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_ICHEC_rcp45_1971-2000_vs_2071-2100.Rdata")


#Extract delta from the point
delta<- t(delta_ICHEC_7100_to_hist_rcp_45)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_ICHEC45<-data.frame(delta_120205)

#Apply delta and add column (120205_ICHEC45_7100) to final
z<-nrow(st1)
i<-1
final$"120205_ICHEC45_7100"<-st1$"RR"

#Apply delta
for (i in 1:z) {
  final$"120205_ICHEC45_7100"[i]=st1$"RR"[i]*(1+(delta_120205_ICHEC45[as.numeric(mv[i]),])/100)
}


#------------------------------------------------ICHEC RCP 8.5--------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_ICHEC_rcp85_1971-2000_vs_2071-2100.Rdata")


#Extract delta from the point
delta<- t(delta_ICHEC_7100_to_hist_rcp_85)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_ICHEC85<-data.frame(delta_120205)

#Apply delta and add column (120205_ICHEC85_7100) to final
z<-nrow(st1)
i<-1
final$"120205_ICHEC85_7100"<-st1$"RR"

#Apply delta
for (i in 1:z) {
  final$"120205_ICHEC85_7100"[i]=st1$"RR"[i]*(1+(delta_120205_ICHEC85[as.numeric(mv[i]),])/100)
}


#------------------------------------------------IPSL RCP 8.5---------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_IPSL_rcp85_1971-2000_vs_2071-2100.Rdata")
```

```
#Extract delta from the point
delta<- t(delta_IPSL_7100_to_hist_rcp_85)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_IPSL85<-data.frame(delta_120205)

#Apply delta and add column (120205_IPSL85_7100) to final
z<-nrow(st1)
i<-1
final$"120205_IPSL85_7100"<-st1$"RR"

#Apply delta
for (i in 1:z) {
  final$"120205_IPSL85_7100"[i]=st1$"RR"[i]*(1+(delta_120205_IPSL85[as.numeric(mv[i]),])/100)
}


#-----------------------------------------------MOHC_HADGEM2 RCP 4.5------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_MOHC_HADGEM2_rcp45_1971-2000_vs_2071-2100.Rdata")

#Extract delta from the point
delta<- t(delta_crrm_7100_to_hist_rcp_45)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_MOHC_HADGEM245<-data.frame(delta_120205)


#Apply delta and add column (120205_MOHC_HADGEM245_7100) to final
z<-nrow(st1)
i<-1
final$"120205_MOHC_HADGEM245_7100"<-st1$"RR"

#Apply delta
for (i in 1:z) {
  final$"120205_MOHC_HADGEM245_7100"[i]=st1$"RR"[i]*(1+(delta_120205_MOHC_HADGEM245[as.numeric(mv[i]),])/100)
}

#-----------------------------------------------MOHC_HADGEM2 RCP 8.5----------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_MOHC_HADGEM2_rcp85_1971-2000_vs_2071-2100.Rdata")


#Extract delta from the point
delta<- t(delta_crrm_7100_to_hist_rcp_85)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_MOHC_HADGEM285<-data.frame(delta_120205)

#Apply delta and add column (120205_MOHC_HADGEM285_7100) to final
z<-nrow(st1)
i<-1
final$"120205_MOHC_HADGEM285_7100"<-st1$"RR"

#Apply delta
for (i in 1:z) {
  final$"120205_MOHC_HADGEM285_7100"[i]=st1$"RR"[i]*(1+(delta_120205_MOHC_HADGEM285[as.numeric(mv[i]),])/100)
}

#-----------------------------------------------MPI_ESM RCP 8.5---------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\RR\\All_DELTA\\Pointdelta_MPI_ESM_rcp85_1971-2000_vs_2071-2100.Rdata")


#Extract delta from the point
delta<- t(delta_MPI_ESM_7100_to_hist_rcp_85)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_MPI_ESM85<-data.frame(delta_120205)

#Apply delta and add column (120205_MPI_ESM85_7100) to final
z<-nrow(st1)
i<-1
final$"120205_MPI_ESM85_7100"<-st1$"RR"

#Apply delta
for (i in 1:z) {
```

```
  final$"120205_MPI_ESM85_7100"[i]=st1$"RR"[i]*(1+(delta_120205_MPI_ESM85[as.numeric(mv[i]),])/100)
}

###Save

final<-final[-10958,]

final<-final[,c(-1,-2)]

setwd("C:\\CLIMADOWN/Step4")

write.table(final, file="C:\\CLIMADOWN\\Step4\\120205_DC_RR.csv", col.names = T, na = "NA")
```

Temperature

```
##### SCRIPT 3.1.2

#### Done with ALL MODELS
#### TEMP (Temperature)
#### For 1 point --- 120205_Kjevik
#### OUTPUT: final

rm(list=ls())
library(zoo)

### Read Daily data from 1 station
st1<-read.table ("C:\\CLIMADOWN\\StationData\\120205_Kjevik_Daily_TEMP.csv", sep=";", header=T)

### Create final data.frame
final<-data.frame(as.numeric(rep(0,10958)))
final$date<-as.Date(c(365:11322), origin="1970-01-01")
final$month<-substr(final$date,6,7)
final<-final[,-1]
mv<-format(as.Date(final$date,format="%Y-%m-%d"), "%m")
mv<-as.numeric(mv)

#-----------------------------------------------CNRM RCP 4.5---------------------------------------------#

##Read delta from all points

load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_CNRM_rcp45_1971-2000_vs_2071-2100.Rdata")


    #Extract delta from the point "120205"
    delta<- t(delta_crrm_7100_to_hist_rcp_45)
    deltaf<-data.frame(delta)
    colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
    delta_120205<-deltaf[,"120205"]
    delta_120205_CNRM45<-data.frame(delta_120205)

    #Apply delta and add column (120205_CNRM45_7100) to final
    z<-nrow(st1)
    i<-1

    #Apply delta
    for (i in 1:z) {
      final$"120205_CNRM45_7100"[i]<-st1$"TEMP"[i]+(delta_120205_CNRM45[as.numeric(mv[i]),])
    }

#-----------------------------------------------CNRM RCP 8.5---------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_CNRM_rcp85_1971-2000_vs_2071-2100.Rdata")


    #Extract delta from the point "120205"
    delta<- t(delta_crrm_7100_to_hist_rcp_85)
    deltaf<-data.frame(delta)
    colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
    delta_120205<-deltaf[,"120205"]
    delta_120205_CNRM85<-data.frame(delta_120205)

    #Apply delta and add column (120205_CNRM85_7100) to final
    i<-1

    #Apply delta
    for (i in 1:z) {
      final$"120205_CNRM85_7100"[i]<-st1$"TEMP"[i]+(delta_120205_CNRM85[as.numeric(mv[i]),])
    }

#-----------------------------------------------ICHEC RCP 2.6---------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_ICHEC_rcp26_1971-2000_vs_2071-2100.Rdata")

#Extract delta from the point "120205"
delta<- t(delta_ICHEC_7100_to_hist_rcp_26)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
```

```
delta_120205_ICHEC26<-data.frame(delta_120205)

#Apply delta and add column (120205_ICHEC26_7100) to final
i<-1

#Apply delta
for (i in 1:z) {
  final$"120205_ICHEC26_7100"[i]<-st1$"TEMP"[i]+(delta_120205_ICHEC26[as.numeric(mv[i]),])
}


#------------------------------------------------ICHEC RCP 4.5---------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_ICHEC_rcp45_1971-2000_vs_2071-2100.Rdata")


#Extract delta from the point "120205"
delta<- t(delta_ICHEC_7100_to_hist_rcp_45)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_ICHEC45<-data.frame(delta_120205)

#Apply delta and add column (120205_ICHEC45_7100) to final
i<-1

#Apply delta
for (i in 1:z) {
  final$"120205_ICHEC45_7100"[i]<-st1$"TEMP"[i]+(delta_120205_ICHEC45[as.numeric(mv[i]),])
}

#------------------------------------------------ICHEC RCP 8.5---------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_ICHEC_rcp85_1971-2000_vs_2071-2100.Rdata")

#Extract delta from the point "120205"
delta<- t(delta_ICHEC_7100_to_hist_rcp_85)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_ICHEC85<-data.frame(delta_120205)

#Apply delta and add column (120205_ICHEC85_7100) to final
i<-1

#Apply delta
for (i in 1:z) {
  final$"120205_ICHEC85_7100"[i]<-st1$"TEMP"[i]+(delta_120205_ICHEC85[as.numeric(mv[i]),])
}

#------------------------------------------------IPSL RCP 8.5---------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_IPSL_rcp85_1971-2000_vs_2071-2100.Rdata")

#Extract delta from the point "120205"
delta<- t(delta_IPSL_7100_to_hist_rcp_85)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_IPSL85<-data.frame(delta_120205)

#Apply delta and add column (120205_IPSL85_7100) to final
i<-1

#Apply delta
for (i in 1:z) {
  final$"120205_IPSL85_7100"[i]<-st1$"TEMP"[i]+(delta_120205_IPSL85[as.numeric(mv[i]),])
}


#------------------------------------------------MOHC_HADGEM2 RCP 4.5------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_MOHC_HADGEM2_rcp45_1971-2000_vs_2071-2100.Rdata")

#Extract delta from the point "120205"
delta<- t(delta_crrm_7100_to_hist_rcp_45)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_MOHC_HADGEM245<-data.frame(delta_120205)

#Apply delta and add column (120205_MOHC_HADGEM245_7100) to final
z<-nrow(st1)
i<-1

#Apply delta
for (i in 1:z) {
  final$"120205_MOHC_HADGEM245_7100"[i]<-st1$"TEMP"[i]+(delta_120205_MOHC_HADGEM245[as.numeric(mv[i]),])
}


#------------------------------------------------MOHC_HADGEM2 RCP 8.5------------------------------------------#
```

```
##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_MOHC_HADGEM2_rcp85_1971-2000_vs_2071-2100.Rdata")

#Extract delta from the point "120205"
delta<- t(delta_crrm_7100_to_hist_rcp_85)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_MOHC_HADGEM285<-data.frame(delta_120205)

#Apply delta and add column (120205_MOHC_HADGEM285_7100) to final
i<-1

#Apply delta
for (i in 1:z) {
  final$"120205_MOHC_HADGEM285_7100"[i]<-st1$"TEMP"[i]+(delta_120205_MOHC_HADGEM285[as.numeric(mv[i]),])
}


#------------------------------------------------MPI_ESM RCP 8.5-------------------------------------------#

##Read delta from all points
load("C:\\CLIMADOWN\\Step3.1.1\\TEMP\\All_DELTA\\Pointdelta_MPI_ESM_rcp85_1971-2000_vs_2071-2100.Rdata")

#Extract delta from the point "120205"
delta<- t(delta_MPI_ESM_7100_to_hist_rcp_85)
deltaf<-data.frame(delta)
colnames(deltaf) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))
delta_120205<-deltaf[,"120205"]
delta_120205_MPI_ESM85<-data.frame(delta_120205)

#Apply delta and add column (120205_MPI_ESM85_7100) to final
i<-1

#Apply delta
for (i in 1:z) {
  final$"120205_MPI_ESM85_7100"[i]<-st1$"TEMP"[i]+(delta_120205_MPI_ESM85[as.numeric(mv[i]),])
}

###Save

final<-final[-10958,]
final<-final[,c(-1,-2)]
setwd("C:\\CLIMADOWN/Step4")
write.table(final, file="C:\\CLIMADOWN\\Step4\\120205_DC_TEMP.csv", col.names = T, na = "NA")
```

9.3 Appendix C: Engen-Skaugen method script: precipitation and temperature

The script 3.2 is presented for the station Kjevik (code: 120205) for precipitation and temperature.

Precipitation

```
####SCRIPT 3.2

###Script that calculates the correction for 1 station (120205)
###Script that calculates for all models and scenarios
###Script that calculates for 2071-2100
###Script for precipitation (RR)

#C: RCM daily historical
#D: station daily historical
#E: RCM daily 2071-2100

rm(list=ls())
library(zoo)

#### Starting in the 3rd equation of Engen-Skaugen paper


### READ D

##Obtain "inf.D" from station historical daily data (D)

#Read station historical daily data
D<-read.table("C:\\CLIMADOWN\\StationData\\120205_Kjevik_Daily_RR.csv", header=TRUE, sep=";")

#Add the date to the daily data
D$date<- as.Date(c(365:11323), origin="1970-01-01")
D<-D[,-1] #deleting fake Date
D$RR<-as.numeric(as.character(D[,1]))
D<-D[-10959,]

#Create data.frame "inf.D"
inf.D<-data.frame(as.numeric(1:12))
colnames(inf.D)<-"mean"

#Obtain the mean monthly values from D and store them on data.frame "inf.D"
for(m in 1:12) {
  b.int<-subset(1:nrow(D), as.numeric(format(as.Date(D$date,format="%Y-%m-%d"), "%m"))==m)
  inf.D$mean[m]<-mean(D[c(b.int),"RR"], na.rm=T)
}

#Now obtain standard desviation monthly values and store also on data.frame "inf.D"
for(m in 1:12) {
  b.int<-subset(1:nrow(D), as.numeric(format(as.Date(D$date,format="%Y-%m-%d"), "%m"))==m)
  inf.D$sd[m]<-sd(D[c(b.int),"RR"], na.rm=T)
}

#Vector for all models and scenarios (9)
c1<-c("CNRM_RCP_45/pr_daily_CNRM_rcp45_2071-00","CNRM_RCP_85/pr_daily_CNRM_rcp85_2071-00",
      "ICHEC_RCP_26/pr_daily_ICHEC_rcp26_2071-00","ICHEC_RCP_45/pr_daily_ICHEC_rcp45_2071-
00","ICHEC_RCP_85/pr_daily_ICHEC_rcp85_2071-00",
      "IPSL_RCP_85/pr_daily_IPSL_rcp85_2071-00",
      "MOHC_HADGEM2_RCP_45/pr_daily_MOHC_HADGEM2_rcp45_2071-00","MOHC_HADGEM2_RCP_85/pr_daily_MOHC_HADGEM2_rcp85_2071-00",
      "MPI_ESM_RCP_85/pr_daily_MPI_ESM_rcp85_2071-00")
#Vector for model (9)
c2<-c("CNRM_hist/pr_daily_CNRM_hist_1971-00","CNRM_hist/pr_daily_CNRM_hist_1971-00",
      "ICHEC_hist/pr_daily_ICHEC_hist_1971-00","ICHEC_hist/pr_daily_ICHEC_hist_1971-00","ICHEC_hist/pr_daily_ICHEC_hist_1971-
00",
      "IPSL_hist/pr_daily_IPSL_hist_1971-00",
      "MOHC_HADGEM2_hist/pr_daily_MOHC_HADGEM2_hist_1971-00","MOHC_HADGEM2_hist/pr_daily_MOHC_HADGEM2_hist_1971-00",
      "MPI_ESM_hist/pr_daily_MPI_ESM_hist_1971-00")
#vector for names (9)
c3<-c("CNRM_RCP_45","CNRM_RCP_85",
      "ICHEC_RCP_26","ICHEC_RCP_45","ICHEC_RCP_85",
      "IPSL_RCP_85",
      "MOHC_HADGEM2_RCP_45","MOHC_HADGEM2_RCP_85",
      "MPI_ESM_RCP_85")
```

```
final<-data.frame(c(rep(0,10957)))

#----------------------------------------BEGIN ITERATION FOR----------------------------------------#

y<-1

for(y in 1:9){

    ### READ E

    #Read E
    load(paste("C:/CLIMADOWN/Step3.1.1/RR/", c1[y], ".RData", sep=""))

    #Then put the data in a matrix format so it is readable
    E<-as.data.frame(matrix(t(as.vector(r2)), ncol=121, nrow=10957, byrow=F))

    #Then take the output from Script 1 in which code, lat and long for each of the columns (RCM poin data) is established
    colnames(E) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))

    #Subtract the point that we are interested in
    Ef<-E[,"120205"]
    Ef<-data.frame(Ef)

    #Add the date to the daily data (2071-01-01, 2100-12-31)
    Ef$date<- as.Date(c(36890:47846), origin="1970-01-01")

    #Then We create Ecor
    E<-Ef
    colnames(E)<-c("cor","date")


    ### READ C

    ##Obtain "inf.C" from RCM hist (C)

    #Read the daily data from RCM future:
    load(paste("C:/CLIMADOWN/Step3.1.1/RR/", c2[y], ".RData", sep=""))

    #Then put the data in a matrix format so it is readable
    C<-as.data.frame(matrix(t(as.vector(a)), ncol=121, nrow=10958, byrow=F))

    #Then take the output from Script 1 in which code, lat and long for each of the columns (RCM poin data) is established
    colnames(C) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))

    #Subtract the point that we are interested in
    Cf<-C[,"120205"]
    Cf<-data.frame(Cf)

    #Add the date to the daily data(1971-01-01, 2000-12-31)
    Cf$date<- as.Date(c(365:11322), origin="1970-01-01")
    C<-Cf

    #Create data.frame "inf.C"
    inf.C<-data.frame(as.numeric(1:12))
    colnames(inf.C)<-"mean"

    #Obtain the mean monthly values from C and store them on data.frame "inf.C"
    for(m in 1:12) {
      b.int<-subset(1:nrow(C), as.numeric(format(as.Date(C$date,format="%Y-%m-%d"), "%m"))==m)
      inf.C$mean[m]<-mean(C[c(b.int),"Cf"], na.rm=T)
    }

    #Now obtain standard desviation monthly values and store also on data.frame "inf.C"
    for(m in 1:12) {
      b.int<-subset(1:nrow(C), as.numeric(format(as.Date(C$date,format="%Y-%m-%d"), "%m"))==m)
      inf.C$sd[m]<-sd(C[c(b.int),"Cf"], na.rm=T)
    }


    ### EQUATION 4A of Engen-Skaugen

    ##Calculate g (gamma)
    g=(inf.D$sd)/(inf.C$sd)
    g<-data.frame(g)



#----------------------------------------BEGIN ITERATION ENGEN-SKAUGEN-----------------------------------#

    numi<-0 #number of iterations

    repeat{
```

```
###EQUATION 3 of Engen-Skaugen


#Create a data frame where we are going to put all the mean values of Ecor (We write random numbers inside)
inf.E<-data.frame(as.numeric(1:12))
colnames(inf.E)<-"mean"

#Obtained the mean monthly values from Ecor and store them on data.frame "inf.Ecor"
for(m in 1:12) {
  b.int<-subset(1:nrow(E), as.numeric(format(as.Date(E$date,format="%Y-%m-%d"), "%m"))==m)
  inf.E$mean[m]<-mean(E[c(b.int),"cor"], na.rm=T)
}

#Now obtained standard desviation monthly values and store also on data.frame "inf.Ecor"
for(m in 1:12) {
  b.int<-subset(1:nrow(E), as.numeric(format(as.Date(E$date,format="%Y-%m-%d"), "%m"))==m)
  inf.E$sd[m]<-sd(E[c(b.int),"cor"], na.rm=T)
}

#We are applying the formula (3) of Engen-Skaugen (Our aoutput is e(residual))
z<-nrow(E)
mv<-format(as.Date(E$date,format="%Y-%m-%d"), "%m")
for (i in 1:z){
  E$e[i]=(E$cor[i]-inf.E$mean[as.numeric(mv[i])])/inf.E$sd[as.numeric(mv[i])]
}


### EQUATION 4B of Engen-Skaugen


##Calculate S

S=g*inf.E$sd


### EQUATION 5 of Engen-Skaugen


##Calculate b(beta)
b<-inf.E$mean/inf.C$mean
b<-data.frame(b)


###EQUATION 6b of Engen-Skaugen


PF<-data.frame(E[,1:2])
z<-nrow(PF)
mv<-format(as.Date(PF$date,format="%Y-%m-%d"), "%m")
mv<-as.numeric(mv)

#Calculate PF
i<-1
for (i in 1:z) {
  if (!(E$cor[i]==0)){
    PF$PF[i]=(E$cor[i]-
inf.E$mean[as.numeric(mv[i])])*g[as.numeric(mv[i]),]+(inf.D$mean[as.numeric(mv[i])]*b[as.numeric(mv[i]),])
  } else {
    PF$PF[i]<-0}
}

#Set PF to 0 if they are negative and we add a COUNTERneg
numneg<-0
for (i in 1:z) {
  if(PF$PF[i]<0){
    PF$PF2[i]<-PF$PF[i]*0
    numneg<-numneg+1
  }else if (!(PF$PF[i]<0)){
    PF$PF2[i]<-PF$PF[i]
  }
}

#Calculate current mean and Sd

assign(paste("inf.comp_",c3[y], sep=""),inf.D)
assign(paste("inf.comp_",c3[y], sep=""),cbind(get(paste("inf.comp_",c3[y], sep="")), inf.E$mean))
assign(paste("inf.comp_",c3[y], sep=""),cbind(get(paste("inf.comp_",c3[y], sep="")), S))


#Place the value on E$cor to start another iteration
E$cor<-PF$PF2

#Counting number of iterations
numi<-numi+1
```

```
      if(numneg<219){ #less than 2% of the data negative
        break
      }
    }

#-----------------------------------------------END ITERATION ENGEN-SKAUGEN---------------------------------------#


##Combine to get the final

ff<-PF$PF2
ff<-data.frame(ff)
colnames(ff)<-c3[y]

final<-cbind(final,ff)

}


#----------------------------------------------------END ITERATION FOR--------------------------------------------#

#-----------------------------------------------------SAVE DATA-------------------------------------------------#


##Saving in Step4

final<-final[,-1]
write.table(final, file="C:\\CLIMADOWN\\Step4\\120205_ES_RR.csv", col.names = T, na = "NA")
```

Temperature

```
####SCRIPT 3.2

###Script that calculates the correction for 1 station (120205)
###Script that calculates for all models and scenarios
###Script that calculates for 2071-2100
###Script for precipitation (TEMP)

#C: RCM daily historical
#D: station daily historical
#E: RCM daily 2071-2100
#F: Ah - Difference between station and RCM (Kjevik:12m, ListaFyr:14m, Sirdal:500m)

# Assumption: RCM height is 1.5-10m --> 5.75m
# Hence, AhKjevik: 6.25m, AhListaFyr: 14m, AhSirdal: 494.25m

rm(list=ls())
library(zoo)

#### Starting in the 7th equation of Engen-Skaugen paper


### READ D

##Obtain "inf.D" from station historical daily data (D)

#Read station historical daily data
D<-read.table("C:\\CLIMADOWN\\StationData\\120205_Kjevik_Daily_TEMP.csv", header=TRUE, sep=";")

#Add the date to the daily data
D$date<- as.Date(c(365:11322), origin="1970-01-01")
D<-D[,-1] #deleting fake Date
D$TEMP<-as.numeric(as.character(D[,1]))
D<-D[-10959,]

#Create data.frame "inf.D"
inf.D<-data.frame(as.numeric(1:12))
colnames(inf.D)<-"mean"

#Obtain the mean monthly values from D and store them on data.frame "inf.D"
for(m in 1:12) {
  b.int<-subset(1:nrow(D), as.numeric(format(as.Date(D$date,format="%Y-%m-%d"), "%m"))==m)
  inf.D$mean[m]<-mean(D[c(b.int),"TEMP"], na.rm=T)
}

#Now obtain standard desviation monthly values and store also on data.frame "inf.D"
for(m in 1:12) {
  b.int<-subset(1:nrow(D), as.numeric(format(as.Date(D$date,format="%Y-%m-%d"), "%m"))==m)
  inf.D$sd[m]<-sd(D[c(b.int),"TEMP"], na.rm=T)
}

#Vector for all models and scenarios (9)
c1<-c("CNRM_RCP_45/tm_daily_CNRM_rcp45_2071-00","CNRM_RCP_85/tm_daily_CNRM_rcp85_2071-00",
```

```
      "ICHEC_RCP_26/tm_daily_ICHEC_rcp26_2071-00","ICHEC_RCP_45/tm_daily_ICHEC_rcp45_2071-
00","ICHEC_RCP_85/tm_daily_ICHEC_rcp85_2071-00",
      "IPSL_RCP_85/tm_daily_IPSL_rcp85_2071-00",
      "MOHC_HADGEM2_RCP_45/tm_daily_MOHC_HADGEM2_rcp45_2071-00","MOHC_HADGEM2_RCP_85/tm_daily_MOHC_HADGEM2_rcp85_2071-00",
      "MPI_ESM_RCP_85/tm_daily_MPI_ESM_rcp85_2071-00")
#Vector for model (9)
c2<-c("CNRM_hist/tm_daily_CNRM_hist_1971-00","CNRM_hist/tm_daily_CNRM_hist_1971-00",
      "ICHEC_hist/tm_daily_ICHEC_hist_1971-00","ICHEC_hist/tm_daily_ICHEC_hist_1971-00","ICHEC_hist/tm_daily_ICHEC_hist_1971-
00",
      "IPSL_hist/tm_daily_IPSL_hist_1971-00",
      "MOHC_HADGEM2_hist/tm_daily_MOHC_HADGEM2_hist_1971-00","MOHC_HADGEM2_hist/tm_daily_MOHC_HADGEM2_hist_1971-00",
      "MPI_ESM_hist/tm_daily_MPI_ESM_hist_1971-00")
#vector for names (9)
c3<-c("CNRM_RCP_45","CNRM_RCP_85",
      "ICHEC_RCP_26","ICHEC_RCP_45","ICHEC_RCP_85",
      "IPSL_RCP_85",
      "MOHC_HADGEM2_RCP_45","MOHC_HADGEM2_RCP_85",
      "MPI_ESM_RCP_85")

final<-data.frame(c(rep(0,10957)))

#----------------------------------------BEGIN ITERATION FOR----------------------------------------#

y<-1

for(y in 1:9){

    ### READ E

    #Read E
    load(paste("C:/CLIMADOWN/Step3.1.1/TEMP/", c1[y], ".RData", sep=""))

    #Then put the data in a matrix format so it is readable
    E<-as.data.frame(matrix(t(as.vector(r2)), ncol=121, nrow=10957, byrow=F))

    #Then take the output from Script 1 in which code, lat and long for each of the columns (RCM poin data) is established
    colnames(E) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))

    #Subtract the point that we are interested in
    Ef<-E[,"120205"]
    Ef<-data.frame(Ef)

    #Add the date to the daily data (2071-01-01, 2100-12-31)
    Ef$date<- as.Date(c(36890:47846), origin="1970-01-01")


    ### EQUATION 7 of Engen-Skaugen


    #Apply altitude correction
    z<-nrow(Ef)
    mv<-format(as.Date(Ef$date,format="%Y-%m-%d"), "%m")

    for (i in 1:z){
      Ef$cor[i]<-Ef[i,"Ef"]-(0.65*(6.25/100))
    }
    Ef["Ef"]<-NULL

    #Then We create E$cor
    E<-Ef
    colnames(E)<-c("date","cor")


    ### READ C

    ##Obtain "inf.C" from RCM hist (C)

    #Read the daily data from RCM future:
    load(paste("C:/CLIMADOWN/Step3.1.1/TEMP/", c2[y], ".RData", sep=""))

    #Then put the data in a matrix format so it is readable
    C<-as.data.frame(matrix(t(as.vector(a)), ncol=121, nrow=10958, byrow=F))

    #Then take the output from Script 1 in which code, lat and long for each of the columns (RCM poin data) is established
    colnames(C) <- rownames(read.table("C:\\CLIMADOWN\\Step1\\Output\\RR_final.csv"))

    #Subtract the point that we are interested in
    Cf<-C[,"120205"]
    Cf<-data.frame(Cf)

    #Add the date to the daily data(1971-01-01, 2000-12-31)
    Cf$date<- as.Date(c(365:11322), origin="1970-01-01")
    C<-Cf

    #Create data.frame "inf.C"
    inf.C<-data.frame(as.numeric(1:12))
    colnames(inf.C)<-"mean"

    #Obtain the mean monthly values from C and store them on data.frame "inf.C"
    for(m in 1:12) {
      b.int<-subset(1:nrow(C), as.numeric(format(as.Date(C$date,format="%Y-%m-%d"), "%m"))==m)
      inf.C$mean[m]<-mean(C[c(b.int),"Cf"], na.rm=T)
    }

    #Now obtain standard desviation monthly values and store also on data.frame "inf.C"
    for(m in 1:12) {
```

```
    b.int<-subset(1:nrow(C), as.numeric(format(as.Date(C$date,format="%Y-%m-%d"), "%m"))==m)
    inf.C$sd[m]<-sd(C[c(b.int),"Cf"], na.rm=T)
  }


### EQUATION 9A of Engen-Skaugen

    ##Calculate g (gamma)
    g=(inf.D$sd)/(inf.C$sd)
    g<-data.frame(g)


#---------------------------------------BEGIN ITERATION ENGEN-SKAUGEN----------------------------------#

    #im<-1 #index mean (relations between E$mean and D$mean )
    #isd<-1 #index sd (relations between S and D$sd )

      ###EQUATION 8 of Engen-Skaugen


      #Create a data frame where we are going to put all the mean values of E (We write random numbers inside)
      inf.E<-data.frame(as.numeric(1:12))
      colnames(inf.E)<-"mean"

      #Obtained the mean monthly values from E and store them on data.frame "inf.E"
      for(m in 1:12) {
        b.int<-subset(1:nrow(E), as.numeric(format(as.Date(E$date,format="%Y-%m-%d"), "%m"))==m)
        inf.E$mean[m]<-mean(E[c(b.int),"cor"], na.rm=T)
      }

      #Now obtained standard desviation monthly values and store also on data.frame "inf.E"
      for(m in 1:12) {
        b.int<-subset(1:nrow(E), as.numeric(format(as.Date(E$date,format="%Y-%m-%d"), "%m"))==m)
        inf.E$sd[m]<-sd(E[c(b.int),"cor"], na.rm=T)
      }

      #We are applying the formula (8) of Engen-Skaugen (Our aoutput is e(residual))
      z<-nrow(E)
      mv<-format(as.Date(E$date,format="%Y-%m-%d"), "%m")
      for (i in 1:z){
        E$e[i]=(E$cor[i]-inf.E$mean[as.numeric(mv[i])])/inf.E$sd[as.numeric(mv[i])]
      }


      ### EQUATION 9B of Engen-Skaugen


      ##Calculate S

      S=g*inf.E$sd


      ### EQUATION 10 of Engen-Skaugen


      ##Calculate b(beta)
      b<-inf.E$mean-inf.C$mean
      b<-data.frame(b)


      ###EQUATION 11b of Engen-Skaugen


      TF<-data.frame(E[,1:2])
      z<-nrow(TF)
      mv<-format(as.Date(TF$date,format="%Y-%m-%d"), "%m")
      mv<-as.numeric(mv)

      #Calculate TF
      i<-1
      for (i in 1:z) {
        if (!(E$cor[i]==0)){
          TF$TF[i]=(E$cor[i]-
inf.E$mean[as.numeric(mv[i])])*g[as.numeric(mv[i]),]+(inf.D$mean[as.numeric(mv[i])]+b[as.numeric(mv[i]),])
        } else {
          TF$TF[i]<-0}
      }

      ##Calculate current mean and Sd
      assign(paste("inf.comp_",c3[y], sep=""),inf.D)
      assign(paste("inf.comp_",c3[y], sep=""),cbind(get(paste("inf.comp_",c3[y], sep="")), inf.E$mean))
      assign(paste("inf.comp_",c3[y], sep=""),cbind(get(paste("inf.comp_",c3[y], sep="")), S))

      #im
      assign(paste("im_",c3[y], sep=""),as.numeric(mean(inf.E$mean-inf.D$mean)))

      #isd
      assign(paste("isd_",c3[y], sep=""),mean(t(S)/inf.D$sd))


#----------------------------------------------END ITERATION ENGEN-SKAUGEN---------------------------------------#

##Combine to get the final

ff<-TF$TF
ff<-data.frame(ff)
```

```
colnames(ff)<-c3[y]

final<-cbind(final,ff)

}

#---------------------------------------------------END ITERATION FOR--------------------------------------------#

#----------------------------------------------------SAVE DATA---------------------------------------------------#


##Saving in Step4

final<-final[,-1]
write.table(final, file="C:\\CLIMADOWN\\Step4\\120205_ES_TEMP.csv", col.names = T, na = "NA")
```

9.4 Appendix D: Old scenarios script

The script 3.3 is presented below.

```
##### SCRIPT 3.3

#### OLD SCENARIOS DATA is loaded and should be put in a way that will be later for comparison later.
#### For 3 point (120205_Kjevik), (120619_Listafyr), (123165_Sirdal)
#### Each point has 2 OLD SCENARIOS: A2, B2

#### OUTPUTS: 6 data.frame/zoo LEVELS: For point and for RR/TEMP

rm(list=ls())
library(zoo)

#-------------------------------------------120205_Kjevik----------------------------------------------#

### RR

  ### A2
  #Read data
  kjevik_RR<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\120205_Kjevik_A2_2071-2100_RR.csv", sep=";", header=T)
  colnames(kjevik_RR)<-"120205_A2"

  ### B2
  #Read data
  a<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\120205_Kjevik_B2_2071-2100_RR.csv", sep=",", header=T)
  colnames(a)<-"120205_B2"
  #Add column
  kjevik_RR<-cbind(kjevik_RR,a)

### TEMP

  ### A2
  #Read data
  kjevik_TEMP<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\120205_Kjevik_A2_2071-2100_TEMP.csv", sep=";", header=T)
  colnames(kjevik_TEMP)<-"120205_A2"

  ### B2
  #Read data
  a<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\120205_Kjevik_B2_2071-2100_TEMP.csv", sep=",", header=T)
  colnames(a)<-"120205_B2"
  #Add column
  kjevik_TEMP<-cbind(kjevik_TEMP,a)

#-------------------------------------------120619_Listafyr----------------------------------------------#

### RR

  ### A2
  #Read data
  Listafyr_RR<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\120619_Listafyr_A2_2071-2100_RR.csv", sep=";", header=T)
  colnames(Listafyr_RR)<-"120619_A2"

  ### B2
  #Read data
  a<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\120619_Listafyr_B2_2071-2100_RR.csv", sep=",", header=T)
  colnames(a)<-"120619_B2"
  #Add column
  Listafyr_RR<-cbind(Listafyr_RR,a)

### TEMP

  ### A2
  #Read data
  Listafyr_TEMP<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\120619_Listafyr_A2_2071-2100_TEMP.csv", sep=";", header=T)
  colnames(Listafyr_TEMP)<-"120619_A2"

  ### B2
  #Read data
  a<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\120619_Listafyr_B2_2071-2100_TEMP.csv", sep=",", header=T)
  colnames(a)<-"120619_B2"
  #Add column
  Listafyr_TEMP<-cbind(Listafyr_TEMP,a)

#-------------------------------------------123165_sirdal----------------------------------------------#

### RR

  ### A2
  #Read data
  Sirdal_RR<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\123165_Sirdal_A2_2071-2100_RR.csv", sep=";", header=T)
  colnames(Sirdal_RR)<-"123165_A2"

  ### B2
  #Read data
  a<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\123165_Sirdal_B2_2071-2100_RR.csv", sep=",", header=T)
```

```
  colnames(a)<-"123165_B2"
  #Add column
  Sirdal_RR<-cbind(Sirdal_RR,a)


### TEMP

  ### A2
  #Read data
  Sirdal_TEMP<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\123165_Sirdal_A2_2071-2100_TEMP.csv", sep=";", header=T)
  colnames(Sirdal_TEMP)<-"123165_A2"

  ### B2
  #Read data
  a<-read.table ("C:\\CLIMADOWN\\OldScenariosData\\123165_Sirdal_B2_2071-2100_TEMP.csv", sep=",", header=T)
  colnames(a)<-"123165_B2"
  #Add column
  Sirdal_TEMP<-cbind(Sirdal_TEMP,a)


####Save

setwd("C:\\CLIMADOWN/Step4")

write.table(kjevik_RR, file="C:\\CLIMADOWN\\Step4\\120205_OS_RR.csv", col.names = T, na = "NA")
write.table(kjevik_TEMP, file="C:\\CLIMADOWN\\Step4\\120205_OS_TEMP.csv", col.names = T, na = "NA")

write.table(Listafyr_RR, file="C:\\CLIMADOWN\\Step4\\120619_OS_RR.csv", col.names = T, na = "NA")
write.table(Listafyr_TEMP, file="C:\\CLIMADOWN\\Step4\\120619_OS_TEMP.csv", col.names = T, na = "NA")

write.table(Sirdal_RR, file="C:\\CLIMADOWN\\Step4\\123165_OS_RR.csv", col.names = T, na = "NA")
write.table(Sirdal_TEMP, file="C:\\CLIMADOWN\\Step4\\123165_OS_TEMP.csv", col.names = T, na = "NA")
```

9.5 Appendix E: Comparison downscaled data from the rest of the stations

Comparison between RCM_{hist} and RCM_{future}, both bias corrected, separated by model are presented for Lista Fyr and Kjevik stations in the next two pages.

Lista Fyr

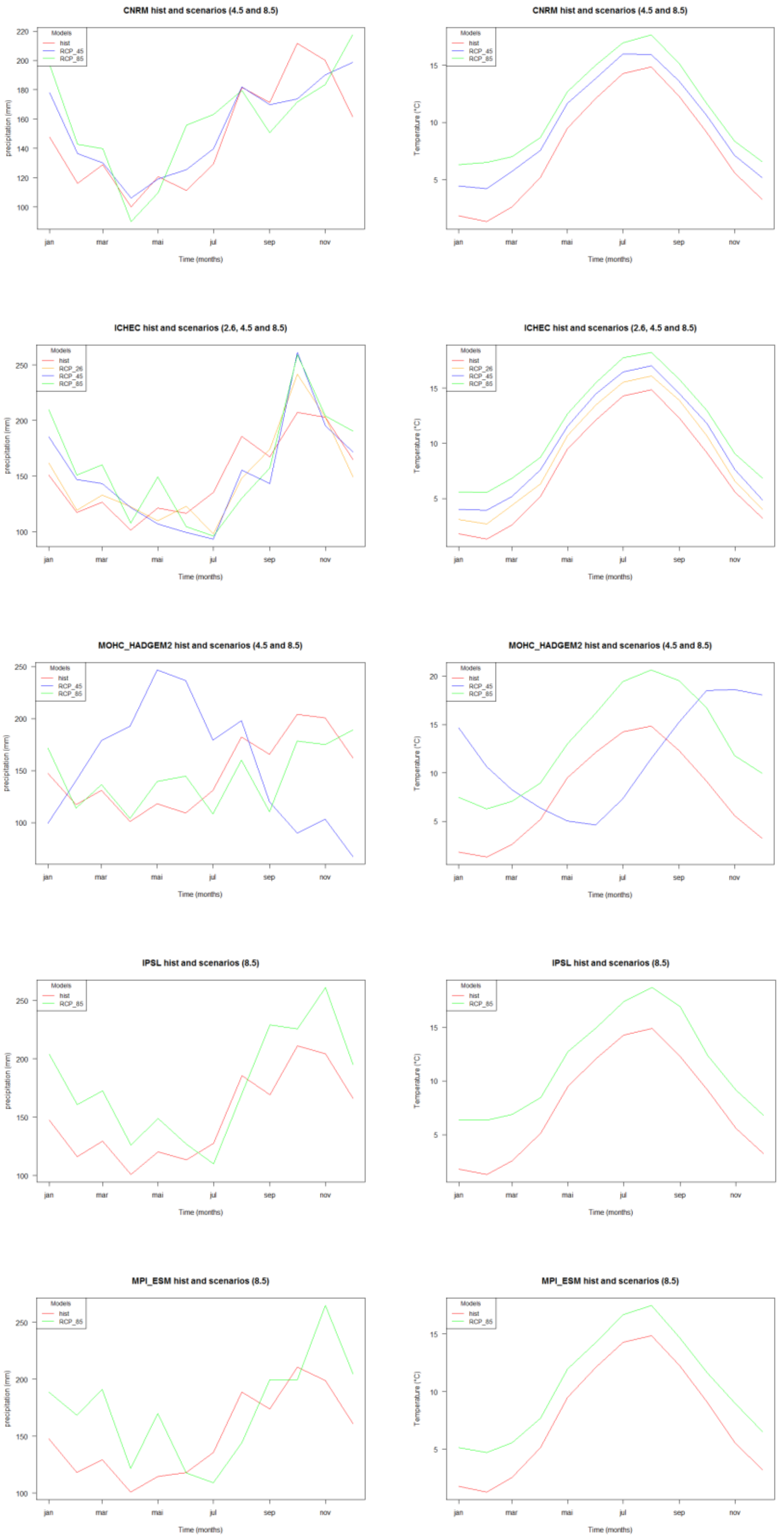


Figure 9-1 RCM$_{hist}$ bias corrected and RCM$_{future}$ bias corrected for all the models and scenarios in Lista Fyr station for precipitation (left) and temperature (right).

Kjevik

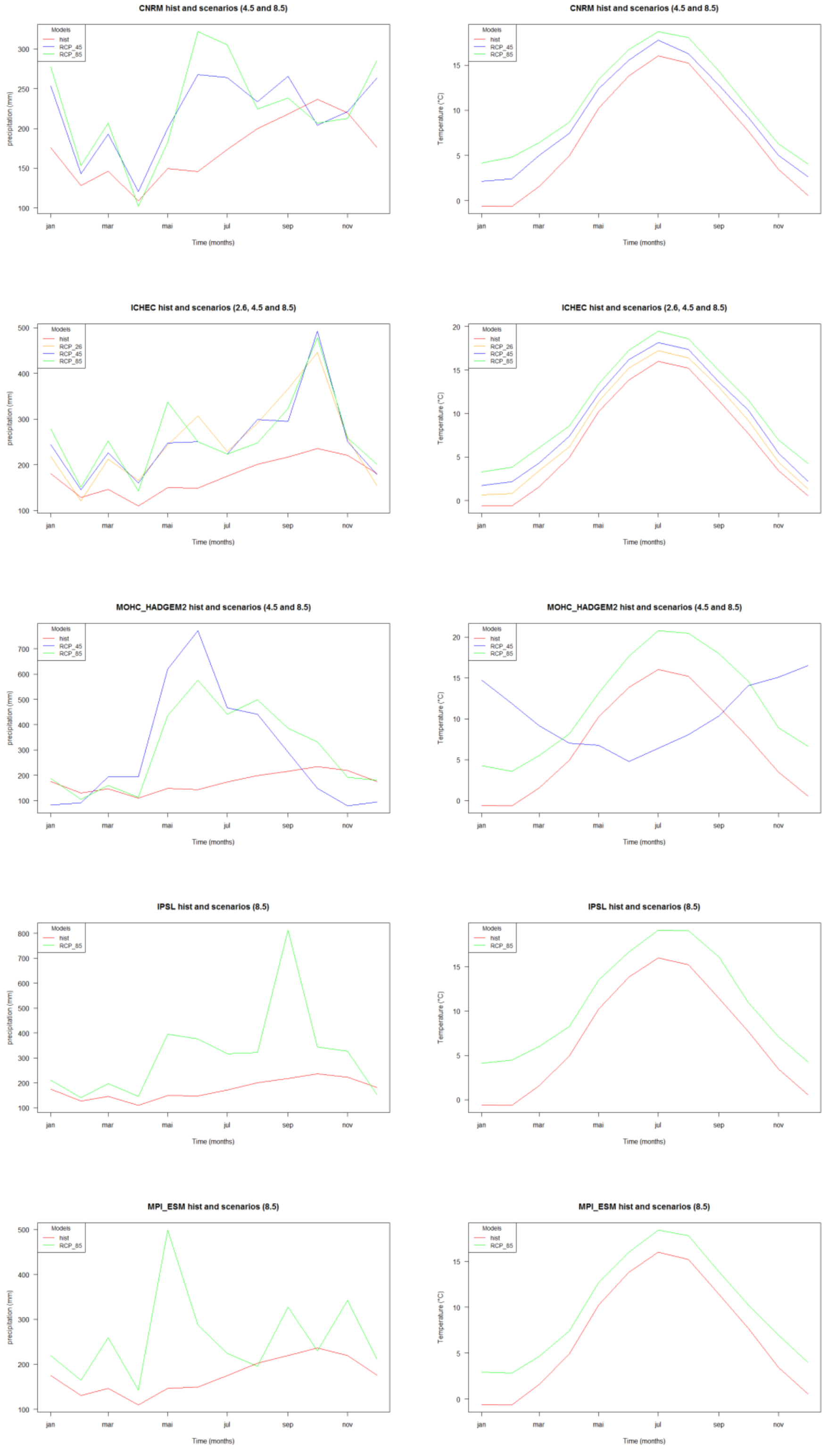


Figure 9-2 RCM_{hist} bias corrected and RCM_{future} bias corrected for all the models and scenarios in Kjevik station for precipitation (left) and temperature (right).

Comparison between RCM_{future} bias corrected and Old scenarios of precipitation and temperature according to each model and scenario.

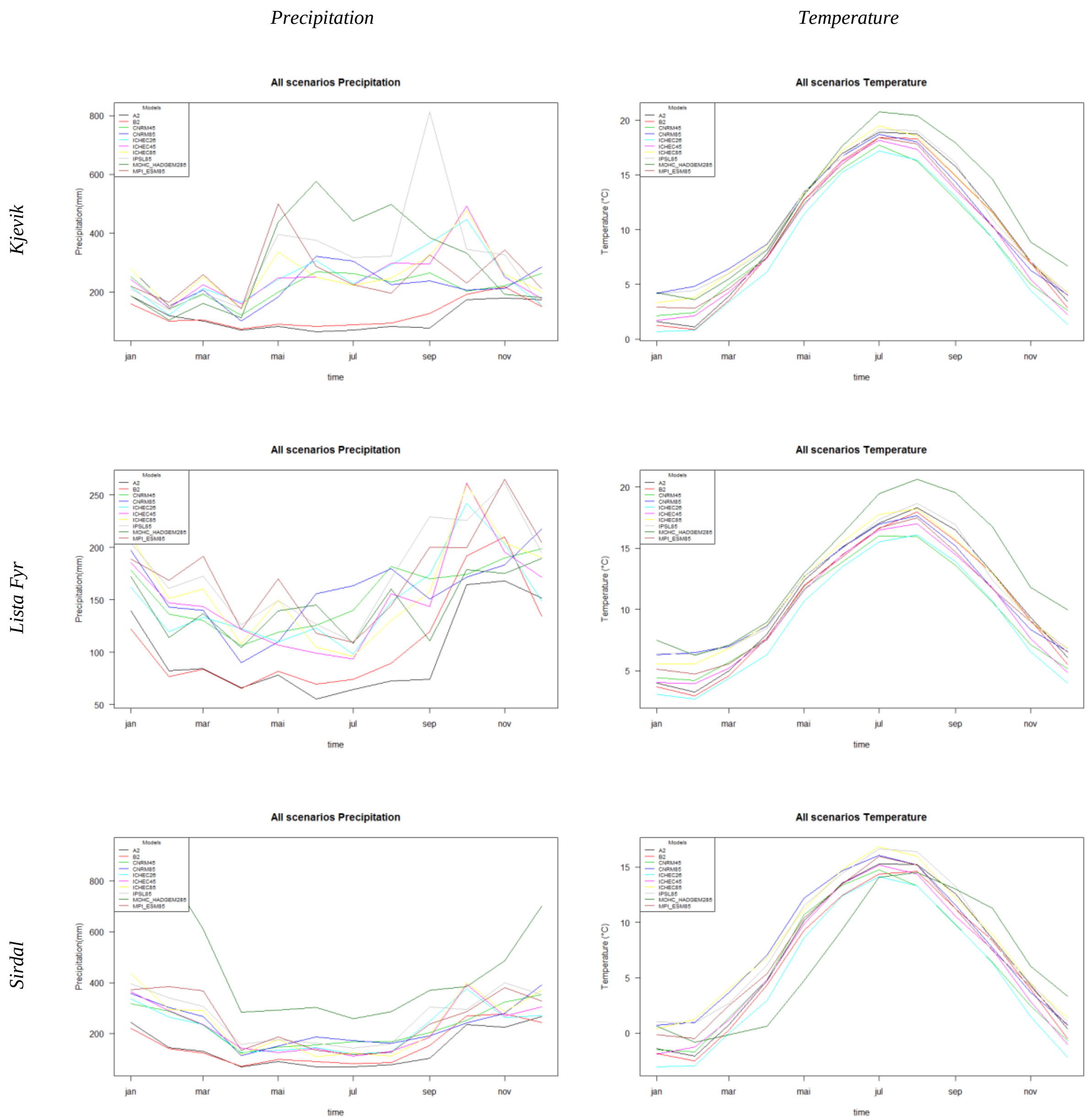


Figure 9-3 Graphs with the mean monthly precipitation values and daily mean temperature of old scenarios and RCM_{future} bias corrected of each station categorized by models and scenarios

Comparison between Delta change and Old scenarios of precipitation and temperature according to each model and scenario.

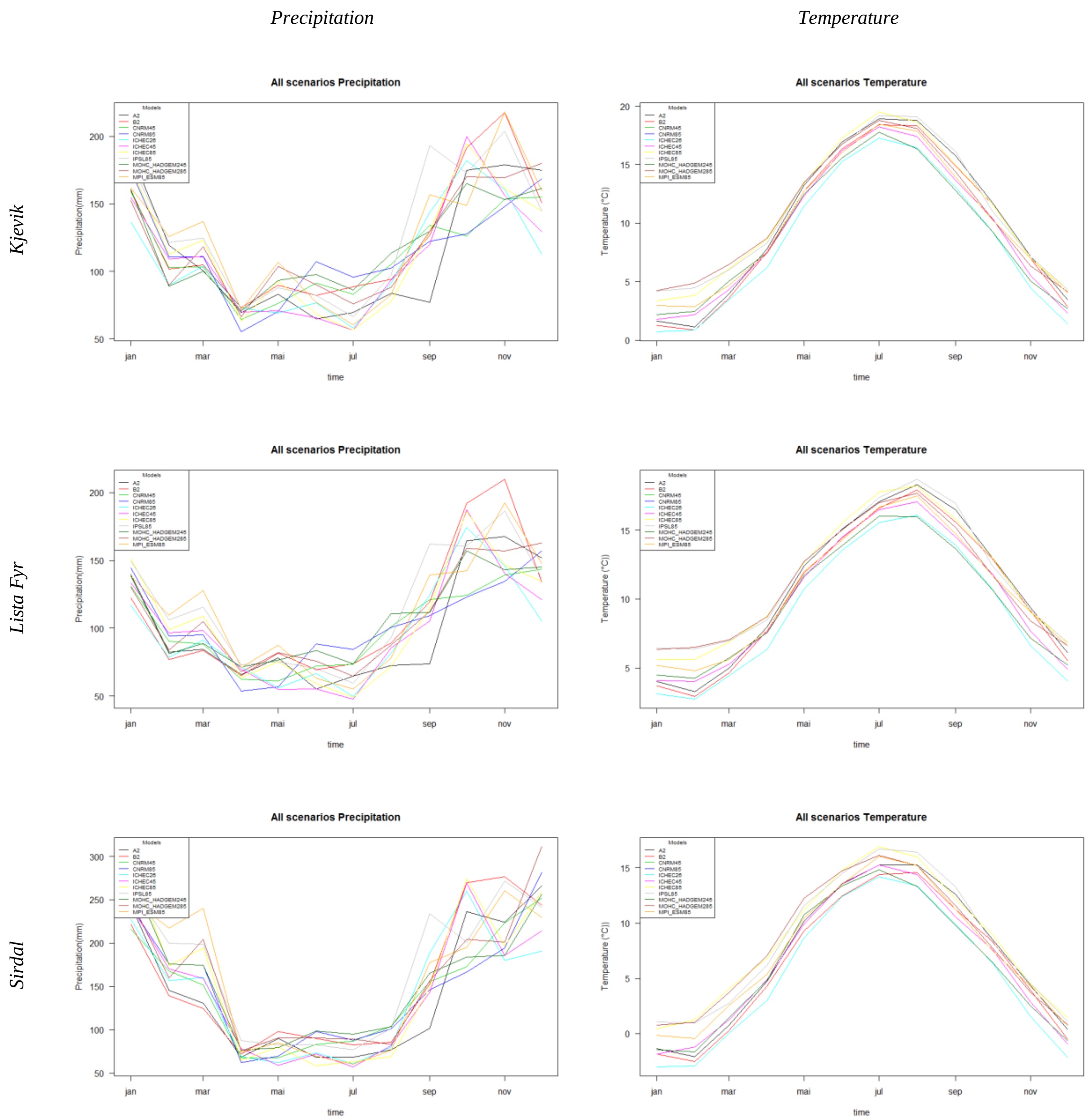
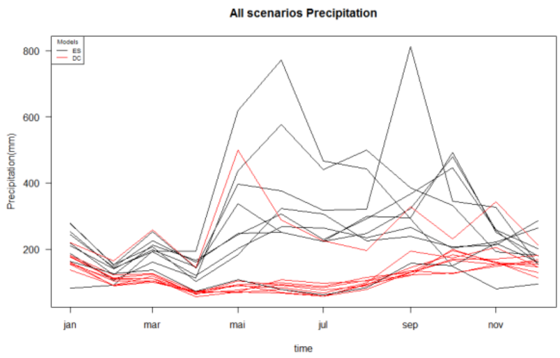


Figure 9-4 Graphs with the mean monthly precipitation values and daily mean temperature of Old scenarios and Delta change of each station categorized by models and scenarios

Comparison between Delta change and RCM_{future} bias corrected of precipitation and temperature for Kjevik and Lista Fyr stations.

Kjevik



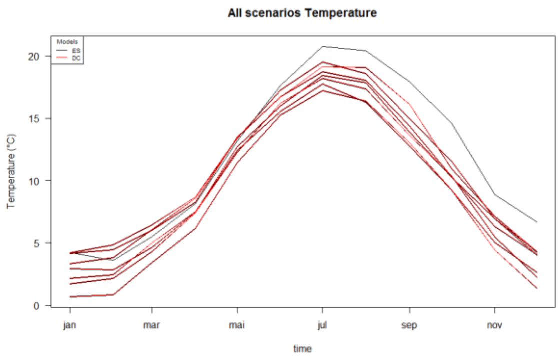
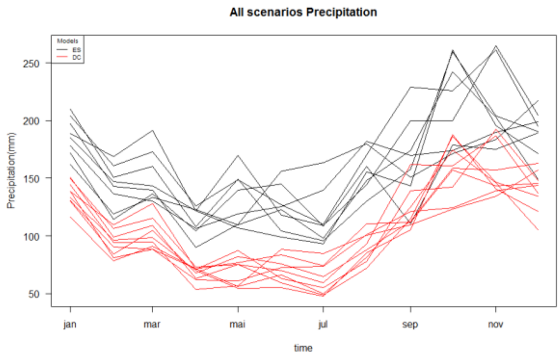


Figure 9-5 Comparison between Delta change and RCM_{future} bias corrected for precipitation (left) and temperature (right) for Kjevik station

Lista Fyr



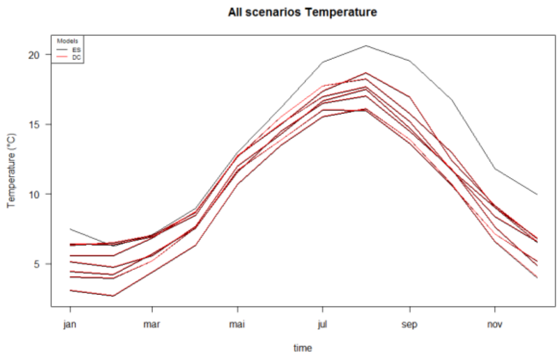


Figure 9-6 Comparison between Delta change and RCM_{future} bias corrected for precipitation (left) and temperature (right) for Lista Fyr station

9.6 Appendix F: Script of comparison

Example for "Script of comparison" of the station Kjevik:

```
##### SCRIPT 4 Comparison

rm(list=ls())
library(zoo)
require(hydroTSM)

setwd("C:\\CLIMADOWN/Step4")

#### READ CSV


### Read Old Scenarios (OS)
k_OS_RR<-read.table(file = "C:\\CLIMADOWN\\Step4\\120205_OS_RR.csv")
k_OS_TEMP<-read.table(file ="C:\\CLIMADOWN\\Step4\\120205_OS_TEMP.csv")

### Read delta Change Applyed (DC)
k_DC_RR<-read.table(file="C:\\CLIMADOWN\\Step4\\120205_DC_RR.csv",na = "NA")
k_DC_TEMP<-read.table(file="C:\\CLIMADOWN\\Step4\\120205_DC_TEMP.csv",na = "NA")

### Read Engen-Skaugen correction (ES)
k_ES_RR<-read.table ("C:\\CLIMADOWN\\Step4\\120205_ES_RR.csv", sep=" ", header=T)
k_ES_TEMP<-read.table ("C:\\CLIMADOWN\\Step4\\120205_ES_TEMP.csv", sep=" ", header=T)

### Read Engen-Skaugen correction historical (ESH)
k_ESH_RR<-read.table ("C:\\CLIMADOWN\\Step4\\120205_ESH_RR.csv", sep=" ", header=T)
k_ESH_TEMP<-read.table ("C:\\CLIMADOWN\\Step4\\120205_ESH_TEMP.csv", sep=" ", header=T)

#### CONVERT INTO ZOO

tf<-seq(as.Date("2071/1/1"), as.Date("2100/12/31"), "days")

c1<-c("RR","TEMP")
c2<-c("OS","DC","ES","ESH")
c3<-c("k","l","s")

i<-1
x<-1
z<-1

for (x in 1:4){
  for (z in 1:2){
    assign(paste("zoo", "k", c2[x], c1[z], sep="_"),zoo(x=get(paste("k", c2[x], c1[z], sep="_")), order.by=tf ))
  }
}

###--------------------------------------------Precipitation (RR)--------------------------------------------###


#### Convert daily data to monthly data per year (Output:zoo)

for(i in 1:3){
  for (x in 1:4){
    for (z in 1:2){
      assign(paste("zoo.m", c3[1], c2[x], c1[1], sep="_"),daily2monthly(get(paste("zoo", c3[1], c2[x], c1[1], sep="_")),
FUN="sum"))
    }
  }
}

#### Convert monthly data per year to mean monthly sums (12 values each column) (Output:matrix)

for(i in 1:3){
  for (x in 1:4){
    for (z in 1:2){
      assign(paste("zoo.12", c3[1], c2[x], c1[1], sep="_"),t(monthlyfunction(get(paste("zoo.m", c3[1], c2[x], c1[1],
sep="_")), FUN="mean")))
    }
  }
}

#### Convert monthly data to year data (Output:data.frame)

for(i in 1:3){
```

```
  for (x in 1:4){
    for (z in 1:2){
      assign(paste("zoo.a", c3[1], c2[x], c1[1], sep="_"),as.data.frame(monthly2annual(get(paste("zoo.m", c3[1], c2[x],
c1[1], sep="_")), FUN="sum")))
    }
  }
}

#### Convert daily data to monthly data per year (Output:data.frame)

for(i in 1:3){
  for (x in 1:4){
    for (z in 1:2){
      assign(paste("zoo.m", c3[1], c2[x], c1[1], sep="_"),as.data.frame(daily2monthly(get(paste("zoo", c3[1], c2[x], c1[1],
sep="_")), FUN="sum")))
    }
  }
}

###--------------------------------------------------TEMP----------------------------------------------------###



#### Convert daily data to monthly data per year (Output:zoo)

for(i in 1:3){
  for (x in 1:4){
    for (z in 1:2){
      assign(paste("zoo.m", c3[1], c2[x], c1[2], sep="_"),daily2monthly(get(paste("zoo", c3[1], c2[x], c1[2], sep="_")),
FUN="mean"))
    }
  }
}

#### Convert monthly data per year to mean monthly sums (12 values each column) (Output:matrix)

for(i in 1:3){
  for (x in 1:4){
    for (z in 1:2){
      assign(paste("zoo.12", c3[1], c2[x], c1[2], sep="_"),t(monthlyfunction(get(paste("zoo.m", c3[1], c2[x], c1[2],
sep="_")), FUN="mean")))
    }
  }
}

#### Convert monthly data to year data (Output:data.frame)

for(i in 1:3){
  for (x in 1:4){
    for (z in 1:2){
      assign(paste("zoo.a", c3[1], c2[x], c1[2], sep="_"),as.data.frame(monthly2annual(get(paste("zoo.m", c3[1], c2[x],
c1[2], sep="_")), FUN="mean")))
    }
  }
}

#### Convert daily data to monthly data per year (Output:data.frame)

for(i in 1:3){
  for (x in 1:4){
    for (z in 1:2){
      assign(paste("zoo.m", c3[1], c2[x], c1[2], sep="_"),as.data.frame(daily2monthly(get(paste("zoo", c3[1], c2[x], c1[2],
sep="_")), FUN="mean")))
    }
  }
}

################################ 1.Comparisson for 1 point between all models of ES with ESH

#### Just for KJEVIK (120205)


###RR

    ##general

    par(mfrow = c(2, 1))


    boxplot(t(zoo.12_k_ESH_RR), main="Kjevik Mean monthly sums ESH",
            xlab="precipitation (mm)", ylab="months", las=1, col="yellow")

    boxplot(t(zoo.12_k_ES_RR), main="Kjevik Mean monthly sums ES",
```

```
        xlab="precipitation (mm)", ylab="months", las=1, col="yellow")

    ab<-cbind(zoo.12_k_ESH_RR,zoo.12_k_ES_RR)

    tfm<-seq(as.Date("2085/1/1"), as.Date("2085/12/31"), "month") # mean of all month of all years

    a<-zoo(ab, tfm)

    par(mfrow = c(1, 1))

    #CNRM
    plot(a[,c(1,6,7)],type="l",plot.type="single", main="CNRM hist and scenarios (4.5 and 8.5)",
        xlab="Time (months)", ylab="precipitation (mm)", las=1, col=c("red","blue", "green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_45","RCP_85"),col=c("red","blue","green"), lty=1,cex=0.9)
    #GRAPH OUTPUT

    #ICHEC
    plot(a[,c(2,8,9,10)],type="l",plot.type="single", main="ICHEC hist and scenarios (2.6, 4.5 and 8.5)",
        xlab="Time (months)", ylab="precipitation (mm)", las=1, col=c("red","orange","blue","green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_26","RCP_45","RCP_85"),col=c("red","orange","blue","green"),
lty=1,cex=0.9)
    #GRAPH OUTPUT

    #IPSL
    plot(a[,c(3,11)],type="l",plot.type="single", main="IPSL hist and scenarios (8.5)",
        xlab="Time (months)", ylab="precipitation (mm)", las=1, col=c("red","green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_85"),col=c("red","green"), lty=1,cex=0.9)
    #GRAPH OUTPUT

    #MOHC_HADGEM2
    plot(a[,c(4,12,13)],type="l",plot.type="single", main="MOHC_HADGEM2 hist and scenarios (4.5 and 8.5)",
        xlab="Time (months)", ylab="precipitation (mm)", las=1, col=c("red","blue", "green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_45","RCP_85"),col=c("red","blue","green"), lty=1,cex=0.9)
    #GRAPH OUTPUT

    #MPI_ESM
    plot(a[,c(5,14)],type="l",plot.type="single", main="MPI_ESM hist and scenarios (8.5)",
        xlab="Time (months)", ylab="precipitation (mm)", las=1, col=c("red","green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_85"),col=c("red","green"), lty=1,cex=0.9)
    #GRAPH OUTPUT


###TEMP

    par(mfrow = c(2, 1))

    boxplot(t(zoo.12_k_ESH_TEMP), main="Kjevik Mean monthly sums Engen-Skaugen Correction historical",
        xlab="temperature (°C)", ylab="months", las=1, ylim=c(0,21), col="yellow")

    boxplot(t(zoo.12_k_ES_TEMP), main="Kjevik Mean monthly sums Engen-Skaugen Correction future 2071-2100",
        xlab="temperature (°C)", ylab="months", las=1, ylim=c(0,21), col="yellow")

    abt<-cbind(zoo.12_k_ESH_TEMP,zoo.12_k_ES_TEMP)

    tfm<-seq(as.Date("2085/1/1"), as.Date("2085/12/31"), "month") # mean of all month of all years

    a<-zoo(abt, tfm)

    par(mfrow = c(1, 1))

    #CNRM
    plot(a[,c(1,6,7)],type="l",plot.type="single", main="CNRM hist and scenarios (4.5 and 8.5)",
        xlab="Time (months)", ylab="Temperature (°C)", las=1, col=c("red","blue", "green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_45","RCP_85"),col=c("red","blue","green"), lty=1,cex=0.9)
    #GRAPH OUTPUT

    #ICHEC
    plot(a[,c(2,8,9,10)],type="l",plot.type="single", main="ICHEC hist and scenarios (2.6, 4.5 and 8.5)",
        xlab="Time (months)", ylab="Temperature (°C)", las=1, col=c("red","orange","blue","green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_26","RCP_45","RCP_85"),col=c("red","orange","blue","green"),
lty=1,cex=0.9)
    #GRAPH OUTPUT

    #IPSL
    plot(a[,c(3,11)],type="l",plot.type="single", main="IPSL hist and scenarios (8.5)",
        xlab="Time (months)", ylab="Temperature (°C)", las=1, col=c("red","green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_85"),col=c("red","green"), lty=1,cex=0.9)
    #GRAPH OUTPUT

    #MOHC_HADGEM2
    plot(a[,c(4,12,13)],type="l",plot.type="single", main="MOHC_HADGEM2 hist and scenarios (4.5 and 8.5)",
        xlab="Time (months)", ylab="Temperature (°C)", las=1, col=c("red","blue", "green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_45","RCP_85"),col=c("red","blue","green"), lty=1,cex=0.9)
```

```
    #GRAPH OUTPUT

    #MPI_ESM
    plot(a[,c(5,14)],type="l",plot.type="single", main="MPI_ESM hist and scenarios (8.5)",
         xlab="Time (months)", ylab="Temperature (°C)", las=1, col=c("red","green"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("hist","RCP_85"),col=c("red","green"), lty=1,cex=0.9)
    #GRAPH OUTPUT


################################ 2.Comparisson for 1 point between all models of ES and OS

#### Just for KJEVIK (120205)

##RR

    tfm<-seq(as.Date("2085/1/1"), as.Date("2085/12/31"), "month") # mean of all month of all years

    av<-cbind(zoo.12_k_OS_RR,zoo.12_k_ES_RR)
    a<-zoo(av, tfm)

    bv<-cbind(apply(av[,c(1,2)],1,mean),apply(av[,c(3,4,5,6,7,8,9,10,11)],1,mean))
    b<-zoo(bv,tfm)


    plot(a,type="l",plot.type="single", main="All scenarios Precipitation",
         xlab="time", ylab="Precipitation(mm)", las=1, col=c(1:8,"darkgreen","brown","orange"),lty=1,lwd=0.05)

legend("topleft",title="Models",legend=c("A2","B2","CNRM45","CNRM85","ICHEC26","ICHEC45","ICHEC85","IPSL85","MOHC_HADGEM245",
"MOHC_HADGEM285","MPI_ESM85"),col=c(1:8,"darkgreen","brown","orange"),lty=1,cex=.6)
    #GRAPH OUTPUT 12 values


    plot(b,type="l",plot.type="single", main="Mean ES and Mean OS Precipitation",
         xlab="time", ylab="Precipitation(mm)", las=1, col=c("blue","red","darkgreen","orange"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("mean old scenarios","Mean Engen-skaugen"),col=c("blue","red"), lty=1,cex=.6)
    #GRAPH OUTPUT 12 values


##TEMP

    avt<-cbind(zoo.12_k_OS_TEMP,zoo.12_k_ES_TEMP)
    a<-zoo(avt, tfm)

    bvt<-cbind(apply(avt[,c(1,2)],1,mean),apply(avt[,c(3,4,5,6,7,8,9,10,11)],1,mean))
    b<-zoo(bvt,tfm)

    plot(a,type="l",plot.type="single", main="All scenarios Temperature",
         xlab="time", ylab="Temperature (°C)", las=1, col=c(1:8,"darkgreen","brown","orange"),lty=1,lwd=0.05)

legend("topleft",title="Models",legend=c("A2","B2","CNRM45","CNRM85","ICHEC26","ICHEC45","ICHEC85","IPSL85","MOHC_HADGEM245",
"MOHC_HADGEM285","MPI_ESM85"),col=c(1:8,"darkgreen","brown","orange"),lty=1,cex=.6)
    #GRAPH OUTPUT 12 values


    plot(b,type="l",plot.type="single", main="Mean ES and Mean OS Temperature",
         xlab="time", ylab="Temperature (°C)", las=1, col=c("blue","red","darkgreen","orange"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("mean old scenarios","Mean Engen-skaugen"),col=c("blue","red"), lty=1,cex=.6)
    #GRAPH OUTPUT 12 values


################################ 3.Comparisson for 1 point between all models ESH and OBS

#### Just for KJEVIK (120205)

### RR

    ### READ D

    ###Obtain "inf.D" from station historical daily data (D)

    ##Read station historical daily data
    D<-read.table("C:\\CLIMADOWN\\StationData\\120205_Kjevik_Daily_RR.csv", header=TRUE, sep=";")

    #3Add the date to the daily data
    D$date<- as.Date(c(365:11323), origin="1970-01-01")
    D<-D[,-1] #deleting fake Date
    D$RR<-as.numeric(as.character(D[,1]))
    D<-D[-10959,]

    ##Create zoo (daily)

    tfd<-seq(as.Date("2071/1/1"), as.Date("2100/12/31"), "days")

    z_obs_d<-zoo(x=D$RR, order.by=tfd)
```

```
    ##Create zoo's to compare

    aux<-daily2monthly(z_obs_d, FUN="mean")

    z_obs_m360_c<-aux*30

    z_obs_m12<-monthlyfunction(z_obs_m360_c, FUN="mean")

    ##Comparison

    #12 values (All models)  zoo.12_k_ESH_RR,z_obs_m12

    val12<-cbind(coredata(z_obs_m12),zoo.12_k_ESH_RR)
    tfm<-seq(as.Date("2085/1/1"), as.Date("2085/12/31"), "month") # mean of all month of all years
    val12<-zoo(x=val12, order.by=tfm)
    plot(val12,type="l",plot.type="single", main="Comparison between all models ESH and OBS",
         xlab="time", ylab="Precipitation (mm)", las=1,
col=c("blue","red","darkgreen","orange","brown","purple"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("Observations","CNRM ","ICHEC","IPSL","MOHC_HADGEM2",
"MPI_ESM"),col=c("blue","red","darkgreen","orange","brown","purple"), lty=1,cex=.8)
    #GRAPH OUTPUT 12 values

    #12 values (mean models) zoo.12_k_ESH_RR_m, z_obs_m12

    zoo.12_k_ESH_RR_m<-apply(zoo.12_k_ESH_RR, 1, mean)
    val12m<-cbind(coredata(z_obs_m12),zoo.12_k_ESH_RR_m)
    val12m<-zoo(x=val12m, order.by=tfm)
    plot(val12m,type="l",plot.type="single", main="Comparison between mean all models ESH and OBS",
        xlab="time", ylab="Precipitation (mm)", las=1, col=c("blue","red"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("Observations","mean all models"),col=c("blue","red"), lty=1,cex=.8)
    #GRAPH OUTPUT 12 values

    #360 values (mean models) zoo.m_k_ESH_RR_m,z_obs_m360_c

    zoo.m_k_ESH_RR_m<-apply(zoo.m_k_ESH_RR, 1, mean)
    val360m<-cbind(coredata(z_obs_m360_c),zoo.m_k_ESH_RR_m)
    tf<-seq(as.Date("2071/1/1"), as.Date("2100/12/31"), "month")
    val360m<-zoo(x=val360m, order.by=tf)
    plot(val360m,type="l",plot.type="single", main="Comparison between mean all models ESH and OBS",
         xlab="time", ylab="Precipitation (mm)", las=1, col=c("blue","red"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("Observations","mean all models"),col=c("blue","red"), lty=1,cex=.8)
    #GRAPH OUTPUT 12 values


###TEMP


    ### READ D

    ###Obtain "inf.D" from station historical daily data (D)

    ##Read station historical daily data
    D<-read.table("C:\\CLIMADOWN\\StationData\\120205_Kjevik_Daily_TEMP.csv", header=TRUE, sep=";")

    #3Add the date to the daily data
    D$date<- as.Date(c(365:11322), origin="1970-01-01")
    D<-D[,-1] #deleting fake Date
    D$TEMP<-as.numeric(as.character(D[,1]))
    D<-D[-10959,]

    ##Create zoo (daily)

    tfd<-seq(as.Date("2071/1/1"), as.Date("2100/12/31"), "days")

    z_obs_d<-zoo(x=D$TEMP, order.by=tfd)

    ##Create zoo's to compare

    z_obs_m360<-daily2monthly(z_obs_d, FUN="mean")

    z_obs_m12<-monthlyfunction(z_obs_m360, FUN="mean")


    ##Comparison

    #12 values (All models)  zoo.12_k_ESH_TEMP,z_obs_m12

    val12<-cbind(coredata(z_obs_m12),zoo.12_k_ESH_TEMP)
    tfm<-seq(as.Date("2085/1/1"), as.Date("2085/12/31"), "month") # mean of all month of all years
    val12<-zoo(x=val12, order.by=tfm)
    plot(val12,type="l",plot.type="single", main="Comparison between all models ESH and OBS",
         xlab="time", ylab="Temperature (°C)", las=1,
col=c("blue","red","darkgreen","orange","brown","purple"),lty=1,lwd=0.05)
```

```
    legend("topleft",title="Models",legend=c("Observations","CNRM ","ICHEC","IPSL","MOHC_HADGEM2",
"MPI_ESM"),col=c("blue","red","darkgreen","orange","brown","purple"), lty=1,cex=.8)
    #GRAPH OUTPUT 12 values

    #12 values (mean models) zoo.12_k_ESH_TEMP_m, z_obs_m12

    zoo.12_k_ESH_TEMP_m<-apply(zoo.12_k_ESH_TEMP, 1, mean)
    val12m<-cbind(coredata(z_obs_m12),zoo.12_k_ESH_TEMP_m)
    val12m<-zoo(x=val12m, order.by=tfm)
    plot(val12m,type="l",plot.type="single", main="Comparison between mean all models ESH and OBS",
         xlab="time", ylab="Temperature (°C)", las=1, col=c("blue","red"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("Observations","mean all models"),col=c("blue","red"), lty=1,cex=.8)
    #GRAPH OUTPUT 12 values


    #360 values (mean models) zoo.m_k_ESH_TEMP_m,z_obs_m360

    zoo.m_k_ESH_TEMP_m<-apply(zoo.m_k_ESH_TEMP, 1, mean)
    val360m<-cbind(coredata(z_obs_m360),zoo.m_k_ESH_TEMP_m)
    tf<-seq(as.Date("2071/1/1"), as.Date("2100/12/31"), "month")
    val360m<-zoo(x=val360m, order.by=tf)
    plot(val360m,type="l",plot.type="single", main="Comparison between mean all models ESH and OBS",
         xlab="time", ylab="Temperature (°C)", las=1, col=c("blue","red"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("Observations","mean all models"),col=c("blue","red"), lty=1,cex=.8)
    #GRAPH OUTPUT 12 values

################################ 4.Comparisson for 1 point between All models DC and OS

#### Just for KJEVIK (120205)

### RR

    tfm<-seq(as.Date("2085/1/1"), as.Date("2085/12/31"), "month") # mean of all month of all years

    an<-cbind(zoo.12_k_OS_RR,zoo.12_k_DC_RR)
    a<-zoo(an, tfm)

    bn<-cbind(apply(an[,c(1,2)],1,mean),apply(an[,c(3,4,5,6,7,8,9,10,11)],1,mean))
    b<-zoo(bn,tfm)


    plot(a,type="l",plot.type="single", main="All scenarios Precipitation",
         xlab="time", ylab="Precipitation(mm)", las=1, col=c(1:8,"darkgreen","brown","orange"),lty=1,lwd=0.05)

legend("topleft",title="Models",legend=c("A2","B2","CNRM45","CNRM85","ICHEC26","ICHEC45","ICHEC85","IPSL85","MOHC_HADGEM245",
"MOHC_HADGEM285","MPI_ESM85"),col=c(1:8,"darkgreen","brown","orange"),lty=1,cex=.6)
    #GRAPH OUTPUT 12 values

    plot(b,type="l",plot.type="single", main="Mean DC and Mean OS Precipitation",
         xlab="time", ylab="Precipitation(mm)", las=1, col=c("blue","red","darkgreen","orange"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("mean old scenarios","Mean Delta change"),col=c("blue","red"), lty=1,cex=.6)
    #GRAPH OUTPUT 12 values

### TEMP

    tfm<-seq(as.Date("2085/1/1"), as.Date("2085/12/31"), "month") # mean of all month of all years

    ant<-cbind(zoo.12_k_OS_TEMP,zoo.12_k_DC_TEMP)
    a<-zoo(ant, tfm)

    bnt<-cbind(apply(ant[,c(1,2)],1,mean),apply(ant[,c(3,4,5,6,7,8,9,10,11)],1,mean))
    b<-zoo(bnt,tfm)

    plot(a,type="l",plot.type="single", main="All scenarios Temperature",
         xlab="time", ylab="Temperature (°C))", las=1, col=c(1:8,"darkgreen","brown","orange"),lty=1,lwd=0.05)

legend("topleft",title="Models",legend=c("A2","B2","CNRM45","CNRM85","ICHEC26","ICHEC45","ICHEC85","IPSL85","MOHC_HADGEM245",
"MOHC_HADGEM285","MPI_ESM85"),col=c(1:8,"darkgreen","brown","orange"),lty=1,cex=.6)
    #GRAPH OUTPUT 12 values

    plot(b,type="l",plot.type="single", main="Mean DC and Mean OS Temperature",
         xlab="time", ylab="Temperature (°C)", las=1, col=c("blue","red","darkgreen","orange"),lty=1,lwd=0.05)
    legend("topleft",title="Models",legend=c("mean old scenarios","Mean Delta change"),col=c("blue","red"), lty=1,cex=.6)
    #GRAPH OUTPUT 12 values
```